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ABSTRACT

We use information from the National Longitudinal Survey of Youth 1979 (NLSY79) and supplementary data sources to examine how cognitive performance, measured at approximately the end of secondary schooling, is related to the labor market outcomes of 20 through 50 year olds. Our estimates control for a wide array of individual and family background characteristics, a limited set of non-cognitive attributes, survey year dummy variables and, sometimes, geographic place effects. The analysis reveals five main findings. First, cognitive performance is positively associated with future labor market outcomes at all ages. The relationship is attenuated but not eliminated by the addition of controls for non-cognitive characteristics, while the inclusion of place effects does not change the estimated associations. Second, the returns to cognitive skill increase with age. Third, the effect on total incomes reflects a combination of positive impacts of cognitive performance for both hourly wages and annual work hours. Fourth, the returns to cognitive skill are greater for women than men and for blacks and Hispanics than for non-Hispanic whites, with differential effects on work hours being more important than corresponding changes in hourly wages. Fifth, the average gains in lifetime incomes predicted to result from greater levels of cognitive performance are only slightly above those reported in prior studies but the effects are heterogeneous, with larger relative and absolute increases, in most models, for nonwhites or Hispanics than for non-Hispanic whites, and higher relative but not absolute returns for women than men.

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We investigate how cognitive performance affects labor market outcomes over the lifecycle. Cognitive skills may be influenced by endowments of what is sometimes termed "intelligence" or IQ (see, e.g., the influential but controversial work of Herrnstein and Murray 1994) but realized cognitive and non-cognitive skills result from a lengthy production process that includes as inputs the aforementioned endowments but also environmental conditions that begin in utero (e.g., Currie 2011; Persico, Figlio and Roth 2016) and continue in childhood through at least secondary school (e.g., Heckman 2000; Heckman 2007). Differences in cognitive performance are important. For example, Neal and Johnson (1996) found that heterogeneity in pre-labor market cognitive skills explains all of the subsequent wage gap between black and white women and around three-quarters of the corresponding differential between black and white men.[1] To the extent that cognitive performance is affected by environmental conditions that are malleable, policies that change such conditions may yield large benefits.

Multiple difficulties arise when attempting to determine how improved cognitive performance affects future labor market outcomes. First, when should cognitive skills be measured? For some early interventions (e.g., policies affecting breastfeeding, infant nutrition, or early childcare), it may be appropriate to evaluate cognitive performance at the time of school entry, or even earlier. Such assessments may be incomplete or otherwise flawed, however, if some of the initial benefits "fade away", or if there are dynamic complementarities, such that initial gains increase the marginal productivity of later investments (Cunha and Heckman, 2007). Our strategy is to examine effects of cognitive performance measured between the ages of 16 and 23, reflecting skills before or shortly after labor market entry.

Second, when should one assess labor market outcomes? Prior investigations have frequently focused on the late twenties or early thirties (e.g., Salkever 1995; Neal and Johnson

[1] However, Lang and Manove (2011) raise concerns about this interpretation.

1996), largely because of data availability. The age when labor market outcomes are evaluated would not matter if returns to cognitive performance were constant across the lifecycle. However, there are theoretical reasons why this is unlikely and our empirical analysis demonstrates that cognitive skill premia increase with age. We therefore analyze effects from approximately twenty to fifty years of age, and make additional assumptions to estimate returns through age 65.

Third, the best measure of labor market performance is not obvious. Investigators have previously focused on weekly earnings (e.g., Griliches and Mason 1972), annual incomes (e.g., Salkever 1995), and hourly wages (e.g., Neal and Johnson 1996). Wage rates are appealing to the extent they indicate marginal labor productivity, although this requires strong assumptions (i.e., perfectly competitive spot labor markets). Work hours could reflect preferences for leisure versus income that might be influenced by human capital investments that increase cognitive performance. However, differences could also occur if institutional factors (e.g., wage floors or involuntary unemployment), introduce divergences between desired and actual work hours. With this in mind, we separately analyze cognitive performance effects on annual labor incomes and work hours and hourly wage rates, as well as a measure of total (discounted) lifetime labor income.[2]

Lifetime income is of special interest to the extent it provides relatively comprehensive information about the benefits of cognitive skill investments and since it appears in a broad class of policy discussions. For example, the Environmental Protection Agency (EPA) considered estimates of the changes in lifetime earnings in developing regulations of lead in drinking water (Levin 1986) and emissions of lead and mercury (Environmental Protection Agency 1997; 2008; 2011). Academic researchers have similarly evaluated the health effects of fish consumption

[2] Throughout the paper, we use “annual income” to mean the sum of income from wage/salary/tips and income from farm/own business. We also examine effects on “annual earnings”, defined as annual income less farm/own business income. Details are provided below.

using estimates of the effects of IQ on lifetime earnings (Rheinberger and Hammitt 2014; Shimshack and Ward 2010). Lutter and Lutter (2012) argued that the present value of lifetime earnings is the appropriate measure to value cognitive improvements related to breastfeeding.

A well-known challenge in any effort to estimate the returns to cognitive performance is that observed relationships need not reflect causal effects, since a constellation of other factors could have independent confounding effects on labor market outcomes. Our analysis specifically considers the role of two categories of variables that have received considerable attention since most prior research examining the returns to cognitive skill was conducted: 1) non-cognitive traits[3] (especially self-reported perceptions of control and self-esteem), which have been shown to influence later life outcomes; and 2) geographic "place effects", which play a role in determining labor market performance and other measures of adult success.

It is also important to emphasize what we are *not* attempting to do in this paper. First, it is well beyond our scope to provide a full evaluation of the benefits of early life human capital investments. As mentioned, a substantial literature emphasizes the role of non-cognitive traits in determining adult outcomes. To the extent that policies improve *both* cognitive and non-cognitive skills, analyses focusing only on cognitive performance are likely to underestimate total benefits. Second, we do not investigate whether there are heterogeneous returns across types of cognitive skills, although such differences may well exist and a full understanding of them may be important for policy design.

Our main data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). We also use information from the later 1997 cohort of the NLSY (NLSY97) and other data sources. We measure cognitive performance at the ages of 16 to 23, from scores on the Armed

[3] We call these traits skills when the context implies that they are abilities that come, in part, from training or practice.

Forces Qualification Test (AFQT). For labor market outcomes, we examine total labor market incomes or earnings, annual work hours, and hourly wages at ages ranging between 20 and 50. We also calculate lifetime-discounted labor incomes based on earnings reported through ages 48-49 and estimated to age 65. Most of models control for a wide array of individual and family background factors, a limited set of non-cognitive characteristics, as well as survey year fixed-effects. Some models also include controls for geographic place effects or provide estimates for population subgroups.

The analysis reveals five main findings. First, cognitive performance is positively associated with future labor market outcomes at all ages. The relationship is attenuated but not eliminated by adding controls for non-cognitive traits, while the inclusion of place effects has no effect on the estimates. Second, the return to cognitive skills rises with age. Third, the effect on labor incomes reflects a combination of positive impacts on both hourly wages and annual work hours. Fourth, the returns to cognitive performance are greater for females than males, and for blacks or Hispanics than non-Hispanic whites, with differential effects on work hours being more important than corresponding changes in hourly wage rates. Fifth, the average gains in lifetime labor incomes predicted to result from higher levels of cognitive performance slightly higher those obtained by prior studies, and reflect offsetting adjustments. Specifically, previous estimates will tend to be understated because the effects of cognitive performance grow over the lifecycle and prior research has typically focused on relatively younger individuals. On the other hand, controlling for non-cognitive traits reduces the overall effect. In addition, previous research has not emphasized the important heterogeneity of results by sex and race/ethnicity, whereby the returns to cognitive performance are higher for nonwhites than whites and, in percentage terms, for females than males.

I. Conceptual Framework

Annual labor incomes, hours worked and hourly wages at age t, Y_t, are assumed to depend on the stock of human capital, θ_t, according to:

(1) $$Y_t = g(\theta_t)$$

where $\partial g / \partial \theta \geq 0$. The assumption that wages increase with human capital is straightforward, as long as employees capture any of the gains to higher marginal labor products. For work hours, and by inference annual earnings, the relationship is less automatic, but we assume and the empirical analysis confirms that there is a positive effect. In principle, θ refers to all types of human capital; however, we hereafter consider only one component—performance on cognitive tests. This restriction is not problematic as long as the factors influencing cognitive performance are similar to those affecting other types of human capital, like non-cognitive skills.

Cunha and Heckman (2007) provide a simple model of skill formation:

(2) $$\theta_t = f(I_{t-1}, \theta_{t-1}, \kappa) + (1-\rho)\theta_{t-1},$$

where I represents human capital investments during the previous period, κ are time-invariant individual characteristics (e.g., endowments), and ρ is the rate of human capital depreciation. Recursively substituting into earlier ages yields:

(3) $$\theta_t = F(\boldsymbol{I}, \theta_0, \kappa, \rho, t),$$

where θ_0 is the "baseline" stock of human capital and $\boldsymbol{I} = I_0, I_1, \ldots\ I_{t-1}$ represents the stream of investments occurring since the baseline period. We do not observe these investments in our data but assume that they are non-negatively related to baseline cognitive performance.

Cunha and Heckman note that self-productivity arises if:

(4) $$\partial\theta_t / \partial\theta_{t-1} = \partial f(I_{t-1}, \theta_{t-1}, \kappa)/\partial\theta_{t-1} + (1-\rho)\theta_{t-1} > 0,$$

and that there is dynamic complementarity if:

$$(5) \qquad \partial^2 f(I_{t-1}, \theta_{t-1}, \kappa)/\partial\theta_{t-1}\partial I_{t-1} > 0.$$

Self-productivity implies that human capital grows with age and dynamic complementarity means that the productivity of subsequent investments rises with the baseline stock of human capital. Cunha and Heckman, focusing on skill development during childhood, show that these imply that initial differences in human capital grow with age. We postulate that an analogous process exists for adult workers.

Substituting (3) into (1) gives:

$$(6) \qquad Y_t = g(\theta_t) = g(F(\boldsymbol{I}, \theta_0, \kappa, \rho, t)),$$

which shows how the dependent variables at age *t* are related to baseline human capital, θ_0, as well as (unobserved) endowments, subsequent investments and depreciation. A key point is that self-productivity and dynamic complementarity imply that, *ceteris paribus*, initial productivity differences (i.e., differences in baseline human capital) grow with age.

Consider the most straightforward case of hourly wages. With competitive labor markets and symmetric and complete information, employers will pay workers their marginal revenue product. Normalizing human capital to be measured according to the labor market productivity it produces, (6) can be simplified to:

$$(7) \qquad Y_t = \theta_t = F(\boldsymbol{I}, \theta_0, \kappa, \rho, t).$$

However, when labor markets are not perfectly competitive or employers do not have perfect information about worker productivity, the situation is more complicated.

Altonji and Pierret (2001) and Lange (2007) emphasize that employers gradually learn about worker productivity. In this case, the correlation between cognitive performance and wages (the outcome they examine) is likely initially to be quite low. However, as individuals gain experience, employers learn about their true productivity, so that the association between productivity and wages strengthens. In the context of the model described above, this provides an additional reason, beyond self-productivity or dynamic complementarity, why the labor market consequences of baseline differences in cognitive performance are likely to increase with age.

The situation for work hours is more complicated. With a completely flexible labor market, it is not clear why baseline or subsequent levels of cognitive performance should be related to hours worked, although a positive association might occur if, for instance, persons with high marginal utilities of income (relative to leisure) tend also to invest heavily in human capital. Holding underlying preferences constant, institutional factors may cause individuals with lower levels of cognitive performance to work relatively few hours. For example, minimum wages and other rigidities might prevent wages from falling to the level where labor supply and demand clear for such individuals. Similarly, the availability of transfer payments or alternative sources of financial support (including from other household members) might raise the reservation wages of less skilled workers, resulting in relatively low work hours. More generally, a substantial literature (e.g., Kahn and Lang 1992), suggests that many workers face constraints on hours worked, most commonly resulting in actual work hours being less than preferred levels. For all of these reasons, we hypothesize that high cognitive skill individuals will work more hours than their less skilled counterparts at any point in time, and that differential is likely to increase with age. Notice, also, that this implies that cognitive performance related differences in labor market experience (i.e. total lifetime work hours) are also likely to rise with age, providing another reason why the effects of initial differences in cognitive skills may grow over the lifecycle.[4]

[4] The relationship between baseline cognitive performance and total experience is actually more complicated. If highly skilled individuals also obtain relatively high levels of education (i.e. stay in school until later ages) they may initially have *lower* levels of total labor market experience but will gradually make up for this through their higher annual work hours and, at older ages, are likely to have worked more lifetime hours.

II. Lessons from Prior Research

For a decade or so after the publication of Herrnstein and Murray's (1994) influential book *The Bell Curve*, there was a flurry of research examining how cognitive performance, often referred to as IQ, influences a variety of labor market (and sometimes other) outcomes (Heckman 1995; Murnane, Willett and Levy 1995; Neal and Johnson 1996; Ceci and Williams 1997; Murnane, et al. 2001).[5] There are many controversies surrounding this work, including the heritability of genetic endowments and the extent to which "intelligence" can be characterized by a single measure.[6] We largely sidestep these issues, noting that cognitive performance as measured by test scores almost certainly reflects a combination of endowments and environmental influences, and instead focus on the relationship between cognitive performance at 16-23 years of age and adult labor market outcomes.[7]

As mentioned, assessments of the effects of cognitive skills on economic outcomes over the lifecycle are valuable in a variety of contexts, perhaps most importantly, for the evaluation of the benefits of government policies and interventions (e.g., Levin 1986; Schwartz 1994; Salkever 1995; Environmental Protection Agency 1997; 2008; 2011; Karoly, Kilburn and Cannon 2005). Most of the prior research has, however, at least three shortcomings. First, as highlighted above, the returns to cognitive skill are likely to increase with age, implying that estimates obtained from investigations focusing on relatively young individuals (such as Salkever 1995; and Neal

[5] More limited related earlier research predated Herrnstein and Murray (e.g., Kiker and Condon 1981; Bound, Griliches and Hall 1986).

[6] For instance, Heckman (1995), in his detailed review of Herrnstein and Murray's book noted that "by no means is there agreement in the psychometric literature that one [latent ability] factor is sufficient to 'explain' the data, or that there is just one type of intelligence" (p. 1095). He also notes that measures of IQ indeed predict productivity but with R^2 values much less than one, and that heritability explains 40-80 percent of within-group variability in measures of IQ. For further discussion and evidence, see Cawley et al. (1997).

[7] Neal and Johnson (1996) similarly interpret the Armed Forces Qualification Test (AFQT) scores, which we also use, as a measure of basic "skills" rather than innate intelligence. As further evidence of the malleability of cognitive test scores, Flynn (1987, 2000), highlighted the importance of environmental determinants of IQ by noting gains of roughly three IQ points per decade in different populations around the world.

and Johnson 1996) are likely to understate lifetime benefits. Specifically, Altonji and Pierret (2001), as well as Lange (2007), show that the wage gains associated with higher AFQT scores increase with experience, and Ganzach (2011) similarly uncovers a substantial positive age-wage gradient in the effects of cognitive performance.[8] However, the upper age in all of these studies is fairly low (the middle to late thirties), limiting generalizability of the results and, with the exception of Ganzach (2011), estimating the effects of cognitive skill was not the primary research question.[9]

Zax and Rees (2002) provide a rare counterexample of research focusing on changes over lifecycle in the returns to cognitive skill. They use data from the Wisconsin Longitudinal Study to examine how scores on the Henmon-Nelson Test of Mental Ability at age 17 are related to earnings at the 35 and 53, after controlling for individual factors and characteristics of respondents' communities, schools, peers and friends. They find that cognitive skill effects are overstated when potential confounding factors are insufficiently controlled for and that the estimated impact is almost twice as large at age 53 as at 35. However, their sample is not representative, being restricted to around 3,000 (disproportionately white) males who were seniors in Wisconsin high schools in 1957, and this cohort faced a very different labor market than people born later. A more general limitation of all of these studies is that it is not possible to separately identify age, time and cohort effects (e.g., Hall, Mairesse and Turner 2007), since only single cohorts were examined.

A second issue is that the earlier work does not account for non-cognitive characteristics, which have demonstrated importance in determining labor market outcomes. For example, using

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8 Ganzach's analysis is restricted to persons with *exactly* 12 years of schooling, which is likely to omit that portion of the cognitive performance effect that operates through increases in educational attainment.

9 Altonji and Pierret (2001) and Lange (2007) are primarily interested in understanding the process by which employers learn about the productivity of their employees.

NLSY79 data (but with outcomes measured only to around age 30), Heckman, Stixrud and Urzua (2006) indicate that non-cognitive traits are at least as important as cognitive skills in determining measures of economic success, such as wages, education and choice of occupation.[10] Analyzing three different data sets, Cunha, Karahan and Soares (2011) emphasize the importance of both cognitive and non-cognitive skills. Interestingly, they find that the returns to non-cognitive characteristics remained fairly constant across time periods, while returns to cognitive skills vary in ways consistent with patterns of education-related wage premia.[11] To the extent that the same processes affecting cognitive performance determine non-cognitive characteristics, estimated effects of the former are likely to be overestimated in models containing inadequate controls for the latter.[12]

Third, there is increasing evidence that a wide variety of adult outcomes are partially determined by geographic "place effects". In this vein, Chetty, Hendren and Katz (2016) show that moving to lower poverty areas at young ages (13 or earlier) is associated with increased college education and earnings, along with reductions in rates of single parenthood. Chetty et al. (2016) find that the deleterious effect of low incomes on life expectancy varies substantially across geographic areas. Zax and Rees (2002), indicate that the estimated earnings effects of cognitive skill are attenuated by around one-third with the additional of controls for community, school and peer characteristics.

Our investigation attempts to make progress along all of these dimensions. We examine three types of outcomes – annual labor incomes, annual work hours and hourly wages –

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[10] Non-cognitive traits are proxied by scores on the Rotter Locus of Control and Rosenberg Self-Esteem Scales.

[11] Using one of their data sets, the Panel Study of Income Dynamics, Cunha et al., follow individuals through age 55; however, the sample is quite restricted – being limited to white males with exactly 12 years of education or who are college graduates.

[12] Borghans et al. (2008) discuss how personality traits and related issues in psychology can be incorporated into economic models.

providing important information on the sources of cognitive performance differentials in labor market outcomes. By using NLSY79 data through 2012, we have (in the absence of attrition or nonresponse), data for all respondents from 22 through 48 years of age, supplying information on the evolution of cognitive performance effects over much of the lifecycle. We include an unusually comprehensive set of controls for individual and family characteristics, as well as several non-cognitive traits. We also provide a limited comparison of the age-AFQT gradients using data for the NLSY97 cohort, which surveyed individuals born approximately 20 years after our main sample. The results suggest that our primary findings reflect true age variations in the returns to cognitive skill, rather than a confounding of age with period effects. We use two methods to control for place effects, and determine that these are not of key importance for our analysis. Finally, we split the entire NLSY79 cohort into younger and older individuals and find that effects for persons for whom the AFQT tests were administered before age 19 (and so where scores are less likely to be determined by subsequent labor market or educational experiences), are modestly larger than for the full sample.

III. Empirical Methods

We use straightforward econometric methods. The basic regression specification is:

(8) $$Y_{it} = \alpha + \beta_1 X_i + \beta_2 Z_{it} + \gamma AFQT_i + \mu_{it},$$

where Y_{it} is the labor market for individual i at age t, X is a vector of age-invariant covariates, Z are age-varying regressors, $AFQT$ is our measure of cognitive performance, and μ is an error term. The estimated return on cognitive performance is $\hat{\gamma}$. One condition required for this to be an unbiased estimate is that AFQT scores are uncorrelated with the error term, after conditioning on the other regressors. More extensive controls reduce the potential for omitted variables bias, but the regression will be "over-conditioned" if these covariates are caused by cognitive performance. Thus, for example, we will not include the completed level of education in most of specifications, since this is likely to be strongly influenced by prior cognitive performance. However, we briefly discuss how the results change when schooling is controlled for. All specifications with supplementary covariates (other than AFQT scores) also include survey year dummy variables, to account for year-specific effects. Some models also contain vectors of county characteristics or fixed-effects. Robust standard errors are shown in parentheses in the tables.

When the outcomes are annual incomes, earnings or work hours, we include observations with zero values in our sample and convert the estimated effects to percentage changes as $\hat{\gamma}/\bar{Y} \times 100$, where $\bar{Y}$ is the mean value of the dependent variable.[13] For hourly wages, we estimate log-linear models, using positive wage observations only and interpret the coefficients directly as percentage changes.[14] We also estimate wage models corresponding to those used for incomes, earnings and work hours to make sure that differences in estimated cognitive skill effects are not sensitive to this choice. We then use the age-specific estimates to examine how cognitive performance affects the net present value of discounted lifetime earnings. The procedures for doing so are detailed below.

[13] Alternatives include estimating two-part or Tobit models; however, the interpretation of the age profiles of effects would be less transparent.

[14] Since the estimates of the AFQT effects on wages are small, coefficients from the log wage regressions can directly be interpreted as percentage changes with little loss of accuracy.

IV. Data and Measures

Our primary data source, the NLSY79, sampled individuals born between 1957 and 1964, who were between the ages of 14 and 21 on December 31, 1978.[15] Interviews were conducted annually through 1994 and biennially since then, with data used here through 2012. The initial survey contained a nationally representative sample of 6,111 respondents and supplemental samples of 2,172 blacks, 1,480 Hispanics/Latinos, 1,643 poor whites (non-black/non-Hispanics) and 1,280 military respondents. Most of the military sample was dropped in 1984, as was the entire economically disadvantaged white sample in 1990. We restrict our analysis to the representative sample, except for our investigation of race/ethnicity disparities, where we include the black and Hispanic oversamples.

Surveys were not conducted in odd years after 1993. Therefore, to maintain consistency over time, we analyze data for even numbered survey years between 1980 and 2012, and evaluate effects at two-year age intervals, with the lower of the two years referred to for brevity. Thus, for example, references to "28" year olds actually refer to 28 and 29 year-old respondents. We use data from multiple survey waves to obtain values of age-specific variables. For instance, data on 28 year olds comes from the 1986, 1988, 1990 and 1992 surveys.

In the absence of sample attrition, we would have information available for all 22 through 48 year olds, as well as for some (but not all) 16-20 and 50-54 year olds.[16] Wave-to-wave attrition or nonresponse rates were modest but the lengthy time period does imply a non-trivial loss of respondents. For example, 4,580 (74.9%) of the 6,111 individuals in the original representative sample provided information at age 48. We examine below whether selective attrition raises concern.

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[15] Information on the NLSY79 is available at http://www.bls.gov/nls/nlsy79.htm).

[16] In 1980, the oldest respondents were 23 years old – and so placed into the 22-23 year old age group – while the youngest were 16. In 2012, these individuals were 48 and 55 years old, respectively.

Our measure of cognitive performance is based on the 2006 renormed version of the Armed Forces Qualification Test (AFQT) score. AFQT scores are calculated using information from four of the ten Armed Services Vocation Aptitude Battery (ASVAB) of tests – word knowledge, paragraph comprehension, math knowledge and arithmetic reasoning – which were completed by 94% of the original (1979) sample in 1980.[17] The 2006 version renormed the scores to control for age (in three-month groups) and expressed them in percentiles.[18] We convert these to standardized Z-scores by assuming that the underlying test score distribution was standard normal.[19] For convenience, we multiply the Z-scores by 10, so that a one unit change corresponds to a 0.1 standard deviation change in AFQT. A potential issue is that respondents could be as old as 23 at the time the AFQT test was taken, raising the possibility that scores reflect early labor market as well as pre-labor market experiences. As a robustness check, we estimated models for a "young sample" where all respondents were born after 1961 (and so were 18 or younger when taking the test). The results obtained when doing are similar but slightly larger to the main estimates that included individuals born slightly earlier, as detailed below.

We evaluate five outcomes: annual labor incomes, earnings or work hours, hourly wages, and "lifetime" discounted labor incomes through age 65. We express amounts throughout in 2014 dollars, using the Consumer Price Index to adjust for price changes. Annual earnings include wages, salaries and tips; annual labor income adds in farm and self-employment

[17] The other ASVAB tests measure knowledge and skill related to general science, numerical operations, coding speed, auto and shop information, mechanical comprehension and electronics information.

[18] NLSY79 has three versions of AFQT scores. The earliest used numerical operations instead of mathematical knowledge to compute the final score. The second, used widely in previous literature (e.g., Neal and Johnson 1996), was not age-adjusted. However, Neal and Johnson show that an additional year of schooling increases a respondent's AFQT raw score by 2 to 4 percentage points. For this reason, we use the age-normed third version of the AFQT score. Information on construction of age-adjusted AFQT percentile scores is available at: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/education/aptitude-achievement-intelligence-scores.

[19] AFQT percentile scores range between 0 and 100. For the conversion to Z-scores we winsorize percentile values less than 0.25% and greater than 99.75%.

income.[20] We construct annual hours worked using the NLSY79's weekly work history data. An issue is that some respondents do not report hours worked in some weeks. If data were missing for no more than 10 percent of weeks, we extrapolate using information for weeks that hours were available. If hours were missing in more than 10 percent of weeks, we treat hours as a missing variable. We also do so if reported annual hours worked exceeded 5,200, assuming that these values were erroneous.

Our primary wage variable uses information provided in the NLSY for the main job held in the week prior to the survey, sometimes referred to as the "CPS job", with reported wage rates below $1 or above than $1,000 per hour treated as missing values. We test the robustness of the results to a different hourly wage variable calculated as total earnings for the specified year divided by annual hours worked.[21]

Finally, we calculate lifetime incomes starting at age 20 and continuing through 65. We use data through the 2012 wave, at which point the youngest respondents are 48 years old. For older ages, we use average of incomes at ages 46-47 and 48-49 as the projected income received up through age 65. We then discount the net present value, in 2014 dollars, to the year of the respondent's birth, using a three percent annual real discount rate in our main estimates, but sometimes also using five and seven percent discount rates. We assume that incomes in odd numbered years are in the same as in the preceding even numbered year and interpolated values for up to three missing survey waves. When income information is missing for more than three waves, or at either age 22 or 48, we do not calculate lifetime earnings.

[20] We do not include in these measures transfer payments, such as the earned income tax credit, unemployment insurance benefits, or the federal Temporary Assistance to Needy Families.

[21] Wages based on the work history data cover the entire year, rather than just a single week, but are more likely to be measured with error because of long recall period. Difficulties are also introduced where there are missing data for some weeks or if there are errors in reports of either annual earnings or work hours. Previous research (Duncan and Hill, 1985; Ruhm 1997) provides some indication that work hours may be overstated using the work history data, which should be noted in our evaluation of annual hours, and will also cause hourly wages calculated using the work history data, to be understated.

These estimates of lifetime incomes refer to NLSY respondents born in the late 1950s or early 1960s. To provide calculations of the hypothetical lifetime incomes for persons born more recently, in 2014, we inflate the aforementioned estimates by 65 percent, which represents the growth in average annual real labor incomes of 20-65 year olds occurring between 1961 (the median year of birth for NLSY79 respondents) and 2014, as measured using data from the 1962 and 2015 March Current Population Surveys.[22]

Table 1 provides summary information on the dependent variables at two ages, 28 and 48, as well as the net present value of lifetime incomes through 48 (the last age for which we directly observe income data) and 65 (the lifetime income variable examined below), calculated using a three percent real discount rate. Annual incomes are just shy of $32,000 for 28 year olds and rise to over $51,000 20 years later, with almost all (between 96% and 97%) income derived from earnings. Hourly wages rise more than 30 percent over the two decades; annual work hours grow by a much smaller 4 percent.[23] Discounted lifetime incomes average over $550,000 through age 65.

In addition to AFQT scores, most models include three types of supplementary covariates. The first are individual or family characteristics measured in early in life (and age-invariant in our data) that may cause or be correlated with cognitive performance. These include: gender, race/ethnicity (black or Hispanic versus non-black non-Hispanic), magazines, library cards and newspapers in home at age 14 (3 dummy variables), urban residence at 14, whether or not the respondent and respondent's mother and father are foreign born (3 variables), mother and father's education (< high school graduate, some college, college graduate vs. high school

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[22] Mean annual incomes, in 2014 dollars, grew from $22,999 in 1961 to $37,920 in 2014. These estimates are illustrative only rather than precise since they make several assumptions including that AFQT effects on earnings have not changed over time and that a common inflation factor is correct for all race-sex groups.

[23] The table shows wages based on the CPS job which are higher than those obtained using the work history data, as expected given previously discussed evidence that annual hours may be overstated.

graduate), number of siblings (0, 1, 2, 3, 4, ≥5, missing), and number older siblings (0, 1, 2, 3, ≥4, missing).[24] We sometimes refer to these as “cross-round” variables.

The second set of regressors includes age-varying characteristics such as: marital status (currently married, divorced/separated widowed vs. never married), urban residence, census region (north central, south, west vs. northeast), and survey-year dummy variables. Although many of these covariates are potentially endogenous (i.e., affected by prior cognitive performance) we include them in our preferred models under the belief that they are likely to strongly influence labor market outcomes while being only weakly determined by AFQT scores. However, we also provide evidence that our main results are robust to excluding these variables.

Third, we control for non-cognitive characteristics, reflecting prior evidence (e.g., Heckman and Rubinstein 2001; Heckman et al. 2006; Borghans et al. 2008) that they affect future outcomes and could be correlated with cognitive performance. Specifically, we include scores from the Rotter Locus of Control scale, designed to measure perceived control over one’s own life, the Rosenberg Self-Esteem scale, indicating self-assessed self-esteem, and a sociability variable measuring self-assessments of the degree to which the respondent is shy or outgoing. The Rotter and Rosenberg scales were measured in 1979 and 1980. Sociability was assessed in 1985 but refers to personality at age 6.[25] Summary statistics for the cross-round and non-cognitive variables are provided in Appendix Table A.1; those on the age-varying characteristics,

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[24] Where the number of siblings or older siblings is missing, we put in the mean values for these variables and then create a missing value dummy variable. We also estimated models that controlled for mother’s age at birth but do not include them in our primary specifications because the quality of this variable is low and its inclusion did not affect our results. In addition, we estimated models with height (in inches) included, without changes in our estimates.

[25] The Rotter score was reverse coded so that higher scores indicate greater self-control. The Rotter and Rosenberg scores were age-adjusted by regressing the raw scores on age in months and its square and then normalizing the residuals to have mean of zero and standard deviation of one. Values on the sociability scale ranged between one (extremely shy) and four (extremely outgoing). Since the sociability score could have non-monotonic effects on labor market outcomes, we include a full set of categorical variables in our regression models. For missing values of the Rotter or Rosenberg scores, we code a value of zero and then create a missing value dummy variable.

at ages 28 and 48, are displayed in Appendix Table A.2. Appendix Table B.1 provides additional details on the construction of some variables.

Fourth, we use two strategies to examine whether the estimated effects of cognitive performance change when controlling for geographic factors. The first includes county-level characteristics similar to those documented to be important by Chetty and Hendren (2015). Specifically, we collect county measures for: population density, fraction of black residents, share of families in poverty, income per capita, fraction of children living with two parents, educational attainment among adults, Gini coefficient, and violent (murder, rape, robbery and assault) and property (burglary, larceny and auto-theft) crime rates. In principle, we would like these variables to cover the period of the respondents' childhood. In practice, we are somewhat constrained by data availability and so use information from the decade of the 1970s, when the NLSY79 individuals were in their teens or younger. These data come from various sources and years (see Appendix Table A.3). For some respondents, the full set of county level statistics is not available. Missing data are mainly related to county crime statistics. We drop these observations from the models that include county characteristics, resulting in a sample size decrease of around five percent.[26] Our results do not appear to be sensitive to these exclusions.

As an alternative, we estimated specifications with county fixed-effects. This generally provides a more comprehensive method of controlling for geographic factors, but with a loss of precision for counties with few sample members. For purposes of identification, we restrict this portion of the analysis to persons residing in counties containing five or more survey respondents,

[26] For example, in the lifetime income specifications, restricting the sample to respondents with a full set of county level measures reduces the sample size from 3,950 to 3,740.

reducing sample sizes by about twelve percent.[27] We only observe respondents' county at age 14 and treat this as the county of residence during childhood.

A final set of estimates compares results for the NLSY79 cohort to those obtained using the more recent NLSY97 data, which sampled persons aged 12-16 in 1996.[28] Doing so introduces several complications. Most importantly, since the information collected for the two cohorts is not identical, we select a somewhat restricted set of control variables that are consistent across surveys. These include: sex, race/ethnicity (black, Hispanic, non-black, non-Hispanic), foreign born, urban residence (at age 14 for the NLSY79 and 12 for NSLY97), foreign language spoken at home, parents' education (<high school, high school, some college, college, missing), parents' foreign born, number of siblings (0, 1, 2, 3, 4, 5+, missing). We also include age-varying controls for: residence (urban, rural, missing), region (northeast, north-central, south, west, missing), and marital status (never married, married and spouse present, other, missing). The non-cognitive variables are unavailable for the NLSY97 cohort and so are excluded from these estimates. The age range of the NLSY97 is also obviously more restricted. We have data through 2013, with the youngest respondents being 29 years old at that time. Therefore, we compare AFQT effects of the two cohorts for the age range 20 through 29, using annual (rather than biennial) surveys.[29] Table A.3 provides descriptive statistics for the cross-round variables included when comparing NLSY79 and NLSY97 results.

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[27] For example, in the lifetime income specifications, the sample size falls from 3,950 to 3,475.

[28] See http://www.bls.gov/nls/nlsy97.htm for further information on the NLSY97 survey.

[29] This is feasible because the NLSY79 did not switch to biennial surveys until after 1994, at which point all respondents were older than 29.

V. Annual Labor Income

We begin our empirical examination by investigating how cognitive performance is related to annual labor income at specific ages. We start with parsimonious specifications and then add more comprehensive sets of controls. We use figures to show the full age-profile of estimated cognitive performance effects and provide additional details for specified ages (generally 28, 38 and 48) in tables. The first model includes only AFQT scores. The second adds the cross-round family and individual background characteristics, as well as survey year fixed-effects. The third also incorporates age-varying covariates and the last includes controls for non-cognitive traits. Figure 1 shows point estimates for all ages between 20 and 50. Table 2 supplies point estimates and robust standard errors at 10-year age intervals beginning at 28.

Two patterns are noteworthy. First, in all specifications, the income effects predicted by higher cognitive performance are positive and grow with age, rapidly during the early 20's and more slowly but almost monotonically thereafter, with no evidence of any reversal before at least age 50. Second, the estimated AFQT premia decline with more comprehensive controls, confirming the expectations that: 1) cognitive performance is related to and probably at least partially caused by environmental characteristics at young ages; and 2) both cognitive performance and non-cognitive traits are likely to have substantial effects on future incomes. In our preferred specification, which includes the most comprehensive set of controls, a 0.1 standard deviation increase in cognitive performance is estimated to raise annual incomes by 1.7%, 2.4% and 2.6% at ages 28, 38 and 48, with standard errors of 0.1% to 0.2%. These predicted effects are approximately one-third smaller than when AFQT is the only independent variable and with an attenuation of 10% or more occurring when the non-cognitive variables are added (model 4 versus model 3). This suggests that the payoff to cognitive performance increases with age but is overestimated when confounding factors are inadequately controlled for.

Next we test the robustness of these results to changes in the choice of samples. Figure 2 repeats the findings for the nationally representative sample and adds estimates for a "balanced" sample, consisting of respondents for whom income data are available at age 48, as for a "full sample" that includes the supplemental oversamples of blacks and Hispanics.[30] The "balanced" sample estimates are virtually identical to those obtained from our main specification, indicating that selective attrition is not an issue. Conversely, the returns to cognitive performance increase with the inclusion of the minority oversamples, providing a first indication of greater gains from cognitive skill for blacks or Hispanics than for non-Hispanic whites: a one tenth of a standard deviation increase in AFQT scores raises predicted incomes of the full sample by 2.0%, 2.7% and 3.1% at ages 28, 38 and 48, compared to 1.7%, 2.4% and 2.6% for the nationally representative sample.

The inclusion of place effects has essentially no impact on the estimates. This is shown in Table 3, where columns (1a) and (1b) limit the sample to observations where the full set of data on county characteristics are available and models (2a) and (2b) to persons in counties with at least five observations, permitting the inclusion of county fixed-effects. The estimates with place effects, (1b) and (2b), are virtually the same as those without, (1a) and (2a), and very similar to the main results containing slightly larger samples. For this reason, we exclude geographic place characteristics from the remainder of the analysis.

[30] A true balanced sample would include respondents providing income data in *all* survey waves. What we refer to a balanced sample is more actually one with information provided in at least some (but possibly not all) surveys waves through that age. We choose 48 because this is the oldest at which all respondents are age-eligible to provide data.

We next estimate models for 20-29 year olds using common specifications and controls using data from the NLSY79 and NLSY97 cohorts. The results, summarized in Figure 3, suggest that the returns to cognitive performance are extremely similar across the two cohorts across all of the ages studied, with some possibility of a (statistically insignificantly) higher return for NLSY97 respondents. For example, at age 28, the point estimate (standard error) of the increased income associated with a 0.1 standard deviation rise in AFQT scores was 2.0 (0.2) percent for the later cohort versus 1.7 (0.1) percent for the earlier one.

Substantially larger increases over time in age-specific AFQT effects would have suggested either that: 1) the returns to cognitive performance had risen for all workers (e.g., because of general effects of the computer use in the labor market) or 2) that the returns to cognitive achievement may have increased more for the later than the earlier cohort (e.g., because computers raised the returns to cognitive skill for current younger but not older workers). The first possibility would have suggested that our main specifications (for the NLSY79 cohort) may have overstated age gradients in AFQT effects– because some of what was attributed to age would actually have been due to secular changes in the returns to cognitive skill. However, the similarity of results obtained for common ages across the two cohorts suggest that the age-profiles in our main analysis are unlikely to be seriously biased by either cohort or time effects.

AFQT scores are measured in 1980, at which point NLSY79 respondents were between 16 and 23 years old. Since many of the older sample members are likely to have entered the labor market or post-secondary schooling by this point, measured cognitive performance could reflect the combined influences of pre-labor market and these later experiences. We examine the potential importance of this by estimating separate models for subsamples stratified by whether individuals were born in 1961 or earlier (and so >18 at the time of testing) or 1962 or later (and so ≤18 when tested). Results of these estimates, summarized on Appendix Table B.2, suggest that there were marginally (and statistically insignificantly) higher returns for those tested at younger ages. To the extent this group provides the more conceptually appropriate estimates, our main results may slightly understate the returns to cognitive skill.

VI. Other Labor Market Outcomes

We next examine cognitive performance effects on annual earnings (which exclude income from farming or self-employment), hourly wages and annual work hours. The results of our preferred specification, which includes background, age-varying and non-cognitive skill covariates are summarized in Table 4 and Figure 4, with estimates for total labor market incomes also repeated for purposes of comparison.

Cognitive performance has virtually identical predicted effects on future annual incomes and earnings, which is unsurprising since the latter account for over 95% of the former. At most ages, between two-thirds and three-quarters of the estimated AFQT impact on income operates through hourly wages, with the remainder reflecting differences in annual work hours. We do not know the reasons for these relative contributions, although wages are often taken as an indication of labor productivity and hours as a reflection of tastes for leisure or of labor market constraints. The age-related AFQT gradient is much flatter for work hours, where there is essentially no trend after age 32, than for wages, where the returns to cognitive skill rise at least through the mid-40s.

Our main specifications include log hourly wages on the CPS reference week job. We also separately estimate models with hourly wages calculated as annual earnings divided by annual hours worked. These provided similar predicted cognitive performance effects, although possibly with slightly lower returns at older ages (see Appendix Figure B.2a).[31] We estimate the main wage effects directly from the semi-log equations, with zero values excluded. Conversely, for annual incomes and work hours, percent changes were predicted from linear models that included zeros, with the regression coefficient then divided by the dependent variable mean (and converted to percentages). To insure that the results were not driven by this difference in procedures, wage effects were also estimated using the same method as for incomes and work hours, which yielded very similar patterns to the main models (see Appendix Figure B.2b).[32]

VII. Subgroup Differences

The effects of cognitive performance on adult labor market outcomes vary by sex and race/ethnicity, with larger relative (and often absolute) effects for females than males and minorities than non-Hispanic whites.

Gender effects are summarized in Figure 5 and Table 5. The predicted cognitive skill effect on income is universally larger for women than men, although the differences are not always statistically significant, with particularly pronounced gaps at young ages. For example, a 0.1 standard deviation increase in AFQT scores raises predicted male incomes by 1.0% at age 28 versus 2.9% for women, both with a standard error of 0.2%. By 38 the differential is half as large (1.9% vs. 2.8%) and by 48 it has narrowed further (2.2% vs. 2.9%).

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[31] The estimated AFQT effects are very similar using either method prior to age 38 and possibly slightly (but insignificantly) higher between 38 and 48 when based on reference week wages (see Appendix Figure B.2a). The largest disparity occurred at age 42, where the estimated cognitive skill effect was 1.40 percent using the alternative wage variable and 1.85 percent based on CPS job wages, with standard errors of 0.14 percent and 0.13 percent.

[32] The AFQT wage effects may be marginally but insignificantly higher when using the alternative estimation strategy. The largest difference was at age 46, where direct estimates from the log wage equations indicate that a 0.1 standard deviation increase in AFQT scores raised hourly wages by 1.82 percent, with a standard error of 0.13 percent while, using the alternative method, the estimated wage increase was 2.17 percent, with a standard error of 0.23 percent. We also obtain very robust results for wages and work hours in models that added controls for county characteristics or county fixed-effects.

These gender differences in income effects are largely *not* driven by differences in impacts on predicted hourly wages, where the predicted impact of cognitive performance is marginally (insignificantly) higher for women than men, except at older ages where there is no difference (Figure 5b). For instance, a 0.1 standard deviation rise in AFQT scores predicts 1.1 percent, 1.4 percent and 1.7 percent wage increases for 28, 38 and 48 year old men, compared to 1.5 percent, 1.8 percent and 1.9 percent wage premia for corresponding women.

Instead, the larger returns of cognitive performance for women than men largely operate through work hours, particularly during the middle twenties through middle thirties (Figure 5c). The largest gender gap occurs at age 24, where the 0.1 standard deviation rise in AFQT predicts a 1.3 percent increase women's annual hours versus a 0.1 percent reduction for men. The differences remain statistically significant through age 40, but fall considerably in size (e.g., to 0.8 percent versus 0.4 percent for 44 year olds) beginning in the early thirties.

Larger AFQT effects on work hours but not wages could reflect greater overall wage elasticities of labor supply for women than men; however, this would not explain why gender differences in the effects on hours are particularly concentrated during the middle 20s through late 30s. This might occur because women with high levels of cognitive skill are more likely to delay childbearing, and the associated reductions in labor supply, into these ages. We found some support in the data for this possibility. Specifically, we constructed age-profiles of estimated AFQT effects on the probability that women had infants or young (less than 3 or 6 year old) children in the household, using specifications similar to those above. These indicated that the likelihood of having infants or young children at home decreased with AFQT scores prior to age 30 but with no difference at later ages (Figure A.1).[33]

[33] For example, at age 26, a 0.1 standard deviation increase in AFQT reduced the likelihood of have a child younger than three (six) by 0.4 (0.7) percentage points. We also estimate work hours models with the inclusion of additional

We present race/ethnicity differences in Figure 6 and Table 6. For these specifications, we use the full NLSY79, including the supplemental samples of non-Hispanic blacks (hereafter simply referred to as blacks) and Hispanics, to increase the sample sizes. Effects of cognitive performance on total labor market incomes are largest for blacks and smallest for non-Hispanic whites (hereafter just whites), as shown in Figure 6a. At age 28, a 0.1 standard deviation rise in AFQT predicts a 1.4 percent increase in white labor market incomes, compared to 2.4 percent for Hispanics and 3.0 percent for blacks. These differences remain pronounced throughout the lifecycle, except that the gap for blacks versus Hispanics falls at older ages.

The overall race/ethnicity differences are again dominated by heterogeneity in effects on work hours, rather than hourly wages, which peak in the early thirties (Figures 6b and 6c). For example, a 0.1 standard deviation increase in cognitive skill predicts a 0.5 percent increase in annual work hours for 32-year-old whites versus 1.5 percent and 1.8 percent for Hispanics and blacks. We suspect this occurs because minorities are more constrained (than whites) in being able to work their desired number of hours, particularly at relatively low levels of cognitive performance. It is not clear why these differences should peak around the early thirties, although a possibility is that hours constraints become less binding after this age for all workers.

VIII. Lifetime Income

Finally, we estimate how cognitive performance affects "lifetime" labor incomes, from ages 20 through age 65, expressed in 2014 dollars. Our main calculations assume a three percent real discount rate, are expressed in 2014 dollars, and are discounted to the birth year. Table 7 summarizes the results, again showing estimated effects of a 0.1 standard deviation increase in

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controls for the number of children in the household and an indicator for presence of a child under the age of three. Doing so reduces but does not completely eliminate the gender gap in predicted AFQT score effects (Figure B.3).

AFQT scores, with robust standard errors displayed in parentheses. We also show the lifetime effects predicted for individuals born in 2014 (rather than for births involving the 1979 cohort), estimated by accounting for the growth in real labor incomes occurring between the median birth year of birth for NLSY79 respondents (1961) and 2014.

A 0.1 standard deviation increase in AFQT is associated with a rise of 2.15 percent, or $11,846, in lifetime income through 65 for the average NLSY79 respondent, which translates into an increase of $19,545 for an infant born in 2014. The predicted effect is somewhat larger in absolute terms for men than women ($20,724 versus $16,778 for 2014 births) but since women earn less than men, the percentage growth is substantially larger for females (2.62 percent versus 1.71 percent).

Strikingly, the income gains associated with cognitive skill are higher *in both relative and absolute* terms for blacks and Hispanics than for whites in most specifications. A 0.1 standard deviation increase in AFQT scores is predicted to raise the lifetime earnings of blacks and Hispanics by 3.59 percent and 3.13 percent, compared to 1.92 percent for whites, which translates into dollar increases of $21,626, $23,117 and $18,635 for 2014 births.[34]

We also estimate effects on lifetime earnings using five and seven percent (rather than three percent) real discount rates (see Appendix Tables A.5 and A.6). Higher discount rates imply lower returns to cognitive skill, given that the positive income effects occur in future years. However, the results in percentage terms are not particularly sensitive to the discount rate. For example, the 0.1 standard deviation increase in AFQT scores increases average lifetime incomes by 2.15, 2.03 and 1.89 percent using a three, five and seven percent annual real discount rates.

[34] Two caveats should be noted. First, the race/ethnicity differences in dollar amounts are not always statistically significantly different. Second, when limiting the sample to respondents born after 1961, the percentage gains are larger for blacks than whites (3.23 percent versus 2.28 percent) but the absolute amounts are somewhat smaller ($11,588 versus $13,664).

Conversely, the absolute dollar amounts are much lower with a five or seven than three percent discount rate ($8,436 and $3,842 versus $19,545), as expected since incomes first occur twenty years after the birth. However, the relative and absolute returns to cognitive performance for blacks or Hispanics continue to exceed those for whites when using our main specifications and any of these discount rates.[35]

IX. Discussion

Cognitive performance, as measured by AFQT scores at ages 16-23, yields substantial returns in terms of future labor market performance. While such a finding is not new to us, we improve on prior research in four ways. First, we provide the most comprehensive investigation to date of the role that confounding factors may play in influencing the estimated relationships. Even our “basic” set of individual and family background controls are more comprehensive than those contained in most prior studies. The inclusion of these plus a restricted set of time-varying characteristics attenuates the raw correlation of cognitive skills on future incomes by 25 percent to 30 percent. Non-cognitive characteristics have received considerable attention recently as determinants of adult outcomes, and our estimates indicate that controlling for these results in an additional 5 percent to 10 percent reduction of the predicted AFQT effect. However, our non-cognitive controls are limited, raising the possibility that a fuller accounting for them would further diminish the estimated influence of cognitive performance. Conversely, we obtain no evidence that geographic place effects explain any of the returns to cognitive skill. This may be because our other regressors are sufficiently comprehensive to account for any impacts of the

[35] The results are also robust to a variety of alternative specifications including those that: add geographic place effects; allow for nonlinear effects by controlling for a quadratic in AFQT scores; or exclude extreme values by deleting the top and bottom five or ten percent of lifetime incomes from the analysis.

county characteristics or fixed-effects that we sometimes control for or because we do not control for other more localized geographic determinants (e.g., neighborhood characteristics).

Second, the labor market returns to cognitive performance rise rapidly with age for individuals in their early twenties and with slower growth thereafter. This has several implications. Most prior analyses, because they have focused on relatively young adults, have likely understated the lifetime returns to cognitive skill. Our investigation may continue to underestimate these benefits, although by less than earlier work, since we only observe individuals until around fifty years old. However, it is unclear what the AFQT-income relationship will look like at later ages. For instance, it could flatten since wage growth tends to slow as retirement approaches, or steepen if higher cognitive performance is associated with delayed retirement. The age profiles we do observe are consistent with models emphasizing self-productivity or dynamic complementarity, whereby initial skills beget future skills.

Third, whereas most earlier studies have focused on income or hourly wages, we show that AFQT impacts on work hours are also important. They explain one-quarter to one-third of the income effect and contribute to the greater returns experienced by females, Hispanics or blacks compared to males or whites. Although these results presumably reflect some combination of preferences and constraints, we suspect that the latter may be of particular importance, with higher cognitive performance providing women and minorities with additional protection against the possibility of being unable to work the desired number of hours.

Fourth, we develop estimates that incorporate alternative discount rates. A one-tenth standard deviation gain in AFQT scores boosts predicted discounted lifetime earnings by 2.15 percent, 2.03 percent, and 1.89 percent at discount rates of 3 percent, 5 percent and 7 percent. These roughly correspond to effects per IQ point of 1.43 percent, 1.35 percent, and 1.26

percent.[36] We express our estimates in dollar terms for a 2014 birth cohort by adjusting for real growth in earnings per worker between the average birth year for our respondents and 2014. It is useful to compare the resulting estimates to those used for policy implementation. For example, in its analysis of possible revisions to national standards for airborne lead levels the EPA estimated the lifetime income effects of one increase in IQ point to be between $8,760 and $12,512 (Environmental Protection Agency 2008).[37] Converting these figures to 2014 dollars, using the CPI-U, and discounting them from age 3 to birth (at 3 percent) gives $9,456 and $13,506, respectively. Thus our preferred estimate of $13,030 per IQ point is slightly less than the greater of EPA's previous estimates, using a three percent discount rate.[38] Our estimates are also applicable to a broad variety of policy interventions that may improve cognitive performance, such as interventions to reduce exposure to lead or other neurotoxicants, to improve children's nutrition (e.g., Black 2003), increase breastfeeding (e.g. Victora et al. 2016), or to promote early childhood development (e.g., Stoltzfus 2015, and Karoly et al. 2005).

The estimated returns to cognitive skill are larger for non-Hispanic blacks and Hispanics than for non-Hispanic whites, in both percent and absolute terms, in almost all specifications. This matters in multiple policy arenas including interventions to improve cognitive performance such as early childhood education (e.g., the U.S. Department of Education's program Race to the Top—Early Learning Challenge) or programs to promote breastfeeding (e.g., Victora et al. 2016). Advocates for focusing such interventions on disadvantaged populations often argue that such targeting will improve equity by reducing disparities. Our results suggest an additional efficiency

[36] Since the standard deviation of IQ is 15 points, we convert our AFQT estimates to effects per IQ point by multiplying by 10/15.
[37] The lower estimate was derived from Schwartz (1994) and the higher one from Salkever (1995). Both estimates use a 3 percent discount rate to discount earnings back to age 3.
[38] EPA's estimate also accounts for additional schooling cost savings that accrue if reductions in lead exposure reduce the need for special education classes, which are beyond the scope of our project. EPA also applied estimates of the percentage effects of IQ to the present value of lifetime earnings derived (largely) from data from the Current Population Survey (CPS). We do not use CPS data here but Hafstead and Lutter (2016) pursue such an approach.

argument. Specifically, if the rewards to increased cognitive skills are greater for minorities than whites, and the incremental costs of improving such skills are similar across groups, the net benefits from interventions targeted toward disadvantaged groups will exceed those from more general interventions.

Our findings may also matter for environmental policy because of continuing concerns about environmental lead, a legacy of lead-based paint and leaded gasoline, which have both been federally banned for decades, and lead in drinking water distribution systems.[39] Our work generally updates and improves on prior estimates of the value of IQ gains from reducing exposure to lead but may also be relevant for federal programs promoting environmental justice (e.g., President Obama 2014), because of concerns about disparate impacts of pollution. In particularly, our research suggests that reducing exposure to environmental toxins among African American and Hispanic children may bring about gains in cognitive performance that have larger effects on future earnings than would equivalent comparable gains in cognitive skill for non-Hispanic whites, again providing a potential efficiency argument for focusing environmental interventions on these groups.

Although cognitive performance is an important determinant of labor incomes, we note that it is not the primary source of earnings inequality, which has received a great deal of recent attention (e.g. Freedman, 2016). To demonstrate this, we calculate the variance as well as the 10th, 25th, 75th and 90th percentiles of both actual discounted lifetime incomes and an adjusted measure of counterfactual incomes predicted to occur if all individuals had average (rather than their actual) AFQT scores. Specifically, the adjusted lifetime incomes are:

(9) $$Y'_i = \hat{\alpha} + \hat{\beta}_1 X_i + \hat{\beta}_2 Z_i + \hat{\gamma}\overline{AFQT} + \hat{\mu}_i,$$

[39] Problems with drinking water containing elevated levels of lead from older lead pipes are well-known, following reports from Flint, Michigan, but Olson and Fedinick (2016) show that such problems may affect millions of Americans beyond Flint.

where $\hat{\alpha}$, $\hat{\beta}_1$, and $\hat{\beta}_2$ are regression coefficients, and $\hat{\mu}$ the regression residual, obtained from estimating equation (8), with $\overline{AFQT}$ representing the sample mean cognitive test score.[40] The adjustment has the effect of lowering (raising) the predicted lifetime labor incomes of persons with high (low) cognitive skill because $\hat{\gamma} > 0$.

The variance of adjusted income is 86.5% of the variance of the unadjusted measure, indicating that differences in AFQT scores explain around 14% of the total variation in lifetime labor incomes. The adjusted 75-25 and 90-10 income ratios are 84.8% and 64.4% as large as the unadjusted ratios, with most of the change occurring because the adjustments substantially increase incomes at the bottom of the distribution.[41] In combination, these results suggest that differences in cognitive performance around the time of labor market entry are likely to explain somewhere between one-seventh and one-third of the heterogeneity in discounted lifetime labor incomes.[42]

We conclude by noting two related areas where we perform a preliminary investigation, but where additional research would be worthwhile. First, we examine the extent to which the observed AFQT effects operate through educational attainment, whereby more cognitively skilled individuals obtain more schooling which, in turn, leads to increases in adult wages and work hours.[43] To do so, we estimate our preferred specifications with and without covariates for education (<12, 12-15, 16 and >16 years). Controlling for years of schooling attenuates the

[40] Although the mean AFQT z-score has been normalized to zero, for the slightly restricted sample containing the data needed to calculate lifetime labor income, the average is 0.02 standard deviations above zero.
[41] The unadjusted 10^{th}, 25^{th}, 75^{th} and 90^{th} percentiles of lifetime income are $109,019, $235,015, $710,373 and $1,056,191. Adjusted incomes at these same percentiles are: $160,718, $270,701, $694,248 and $1,002,334.
[42] We emphasize that these results are illustrative only, rather than definitive because, for example, we have not examined differentials at other income percentiles and since cognitive performance may influence some variables (e.g. marital status) included in our prediction equation.
[43] In specifications with controls for cross-round and time-varying effects, as well as non-cognitive test scores, a 0.1 standard deviation increase in AFQT scores predicts a 0.12 year increase in schooling.

estimated AFQT effect on incomes by around 50 percent at most ages (see Appendix Figure B.4), suggesting that this is a mechanism for approximately half of the cognitive performance effect.

Second, our analysis treats cognitive performance as a unified measure, whereas different components may yield disparate returns, as noted, for example, by Cawley et al. (1997) and Murnane et al. (2001). To provide some indication of this heterogeneity, we conduct a preliminary analysis that divides cognitive scores into math and verbal performance measures. The estimates suggest larger returns to math than verbal skills, as well as steeper age-gradients in these returns. We plan to investigate this issue in future research.

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Table 1: Descriptive Statistics for Outcome Variables at Selected Ages

Variable	Mean	Standard Deviation	Mean	Standard Deviation
Time-varying	*28-29 Year Olds*		*48-49 Year Olds*	
Annual Income ($)	31,942	27,714	51,548	65,556
Annual Earnings ($)	31,090	25,280	49,594	62,197
Hourly Wages ($)	1,5.81	1.72	20.55	2.02
Annual Hours	1,703	952	1,754	1,029
	through 48-49		*through 65*	
NPV of Lifetime Income ($)	383,292	304,382	550,351	481,945

Note: Data are from the nationally representative NLSY79 sample. Hourly earnings refer to the CPS job. For time-varying outcome variables, the sample contains 5,311 28-29 year olds and 4,406 48-49 year olds. Sample sizes are 5,016, 5,016, 4,223 and 5,169 for incomes, earnings, wages and work hours of 28-29 year olds. For 48-49 year olds, the corresponding sample sizes are 4,264, 4,264, 3,237 and 4,322. The sample size for the computation of lifetime incomes is 3,950. Values are in 2014 dollars and, for lifetime incomes, obtained using a 3 percent discount rate.

Table 2: Estimated AFQT "Effects" on Annual Labor Income

Age	(1)	(2)	(3)	(4)
28	0.027	0.020	0.019	0.017
	(0.001)	(0.001)	(0.001)	(0.001)
38	0.035	0.027	0.026	0.024
	(0.002)	(0.002)	(0.002)	(0.002)
48	0.042	0.032	0.030	0.026
	(0.002)	(0.002)	(0.002)	(0.002)
Other Covariates	None	Background	Background, Time-Varying	Background, Time-Varying, Non-cognitive

Note: Table shows estimated effects of a 0.1 standard deviation increase in AFQT score for the representative NLSY79 sample, with robust standard errors in parentheses. The ages are two-year groupings beginning with the age listed (e.g., 28 refers to 28-29 year olds). Estimates are obtained from the coefficient on the computed AFQT Z-score regressed on annual incomes (including zeros). These estimates are then divided by the dependent variable mean at the specified age. Multiplying these estimates by 100% gives percentage changes. Supplementary characteristics (other than AFQT) are shown at the bottom of the table. Models (2) through (4) also include survey year fixed-effects.

Table 3: Estimated AFQT “Effects” on Annual Labor Income with Controls for Place Effects

	Sample with Data on County Characteristics		Counties with Five or More Respondents	
Age	(1a)	(1b)	(2a)	(2b)
28	0.019	0.019	0.018	0.018
	(0.002)	(0.002)	(0.002)	(0.002)
38	0.026	0.026	0.024	0.025
	(0.002)	(0.002)	(0.002)	(0.002)
48	0.029	0.030	0.027	0.026
	(0.003)	(0.003)	(0.002)	(0.003)
Place Effects	No	Yes	No	Yes

Note: Table shows estimated effects of a 0.1 standard deviation increase in AFQT score for the representative NLSY79 sample, at different ages, with robust standard errors in parentheses. See note on Table 2 for additional details. All models control for background and time-varying characteristics, non-cognitive scores and survey year fixed-effects. Model (1b) adds controls for county-characteristics measured during the respondent’s childhood and model (2b) controls for county fixed-effects. The samples in models (1a) and (1b) are those for which county characteristics are available; sample sizes are 4,736, 4,240 and 4,030 at ages 28, 38 and 48. The samples in models (2a) and (2b) are counties with data available for five or more NLSY79 respondents, and sample sizes are 4,395, 3,952 and 3,736 for ages 28, 38 and 48.

Table 4: Cognitive Performance Effects on Various Labor Market Outcomes

Age	Annual Labor Income	Annual Earnings	Hourly Wages	Annual Hours
	(1)	(2)	(3)	(4)
28	0.017	0.018	0.013	0.007
	(0.001)	(0.001)	(0.001)	(0.001)
38	0.024	0.024	0.016	0.006
	(0.002)	(0.002)	(0.001)	(0.001)
48	0.026	0.028	0.018	0.009
	(0.002)	(0.002)	(0.001)	(0.001)

Note: See note on Table 2. Table shows estimated effects of a 0.1 standard deviation increase in AFQT score for the representative NLSY79 sample, at different ages, with robust standard errors in parentheses. In addition to AFQT scores, models control for background, age-varying, and non-cognitive characteristics and survey year fixed-effects. Dependent variables are average annual values of incomes, earnings, and work hours, as well as the log of hourly wages on the reference week job. For the annual outcomes, estimates are obtained from the coefficient on the computed AFQT Z-score regressed on annual incomes (including zeros). These estimates are then converted to percentage changes by dividing the estimated effect by the dependent variable mean at the specified age.

Table 5: Cognitive Performance Effects by Gender

	Men			Women		
Age	Annual Labor Income	Hourly Wages	Annual Hours	Annual Labor Income	Hourly Wages	Annual Hours
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
28	0.010	0.011	0.002	0.029	0.015	0.014
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
38	0.019	0.014	0.002	0.028	0.018	0.011
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)
48	0.022	0.017	0.006	0.029	0.019	0.012
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)

Note: See notes on Tables 2 and 4. Table shows estimated effects of a 0.1 standard deviation increase in AFQT score for the representative NLSY79 sample, at different ages, with robust standard errors in parentheses.

Table 6: Cognitive Performance Effects by Race/Ethnicity

Age	Non-Hispanic Whites			Non-Hispanic Blacks			Hispanics		
	Annual Labor Income	Hourly Wages	Annual Hours	Annual Labor Income	Hourly Wages	Annual Hours	Annual Labor Income	Hourly Wages	Annual Hours
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
28	0.014	0.012	0.004	0.030	0.015	0.014	0.024	0.010	0.014
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
38	0.021	0.015	0.005	0.040	0.024	0.012	0.032	0.017	0.013
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
48	0.023	0.018	0.009	0.042	0.020	0.012	0.040	0.026	0.012
	(0.003)	(0.002)	(0.001)	(0.004)	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)

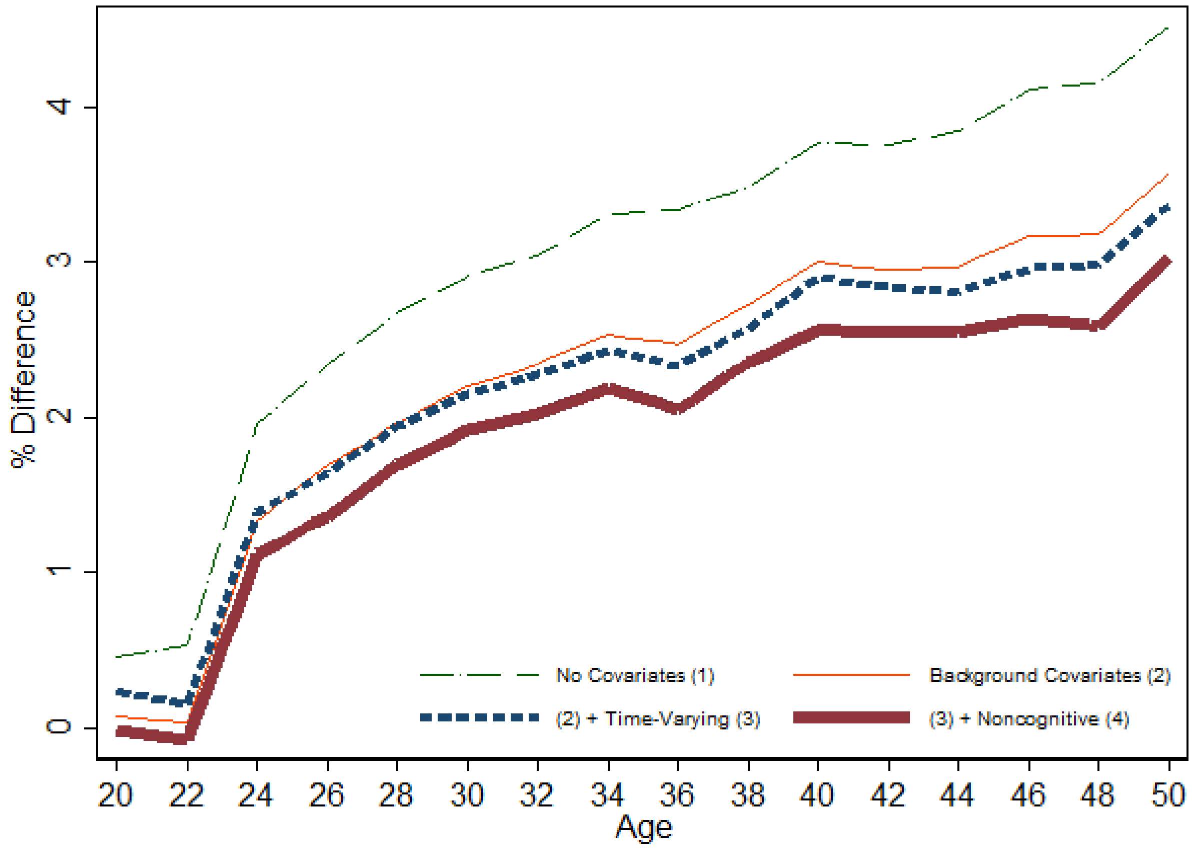
Note: See notes on Tables 2 and 4. Table shows estimated effects of a 0.1 standard deviation increase in AFQT score at different ages, with robust standard errors in parentheses. Non-Hispanic whites in the representative NLSY79 sample are analyzed in models 1a, 2a and 3a, with the oversamples of non-Hispanic Blacks and Hispanics also incorporated in the remaining models.

Table 7: Cognitive Performance Effects on Lifetime Labor Income through Age 65

	All	Men	Women	Non-Hispanic White	Non-Hispanic Black	Hispanic
Percentage Change	2.15% (0.16%)	1.71% (0.21%)	2.62% (0.24%)	1.92% (0.17%)	3.59% (0.28%)	3.13% (0.31%)
Lifetime Incomes NLSY79 Cohort	$11,846 (886)	$12,560 (1489)	$10,168 (905)	$11,294 (1004)	$13,107 (1027)	$14,010 (1361)
Lifetime Incomes 2014 Births	$19,545	$20,724	$16,778	$18,635	$21,626	$23,117
N	3,950	1,860	2,090	3,206	1,892	1,177

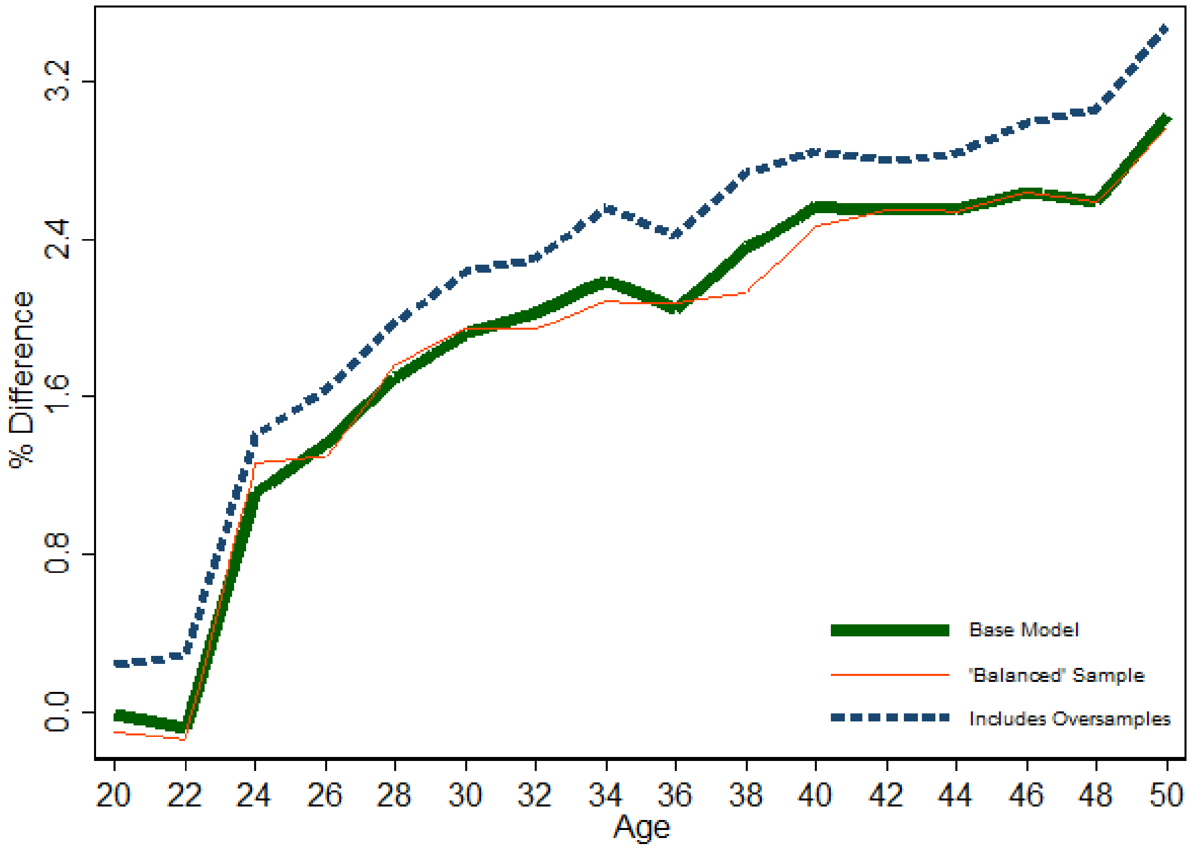
Note: See notes on Tables 2, 5 and 6. Table shows estimated effects of a 0.1 standard deviation increase in AFQT score for the representative NLSY79 sample as a percentage or dollar amount change on the net present value of the sum of annual labor income from age 20 through age 65 for the specified population group. Incomes are discounted to the birth year using an annual real discount rate of three percent and are expressed in 2014-year dollars. For Americans born in 2014, the estimates are inflated by the growth in real earnings occurring from 1961 to 2014. For all individuals, men and women, data are from the nationally representative NLSY79 sample. The race/ethnicity estimates use the full sample, including the supplementary samples of blacks and Hispanics. “Whites” refer to non-black non-Hispanics. In addition to AFQT scores, the models control for background, age-varying, and non-cognitive characteristics and survey year fixed-effects. Robust standard errors are shown in parentheses.

Fig 1: Estimated AFQT "Effects" on Annual Labor Income



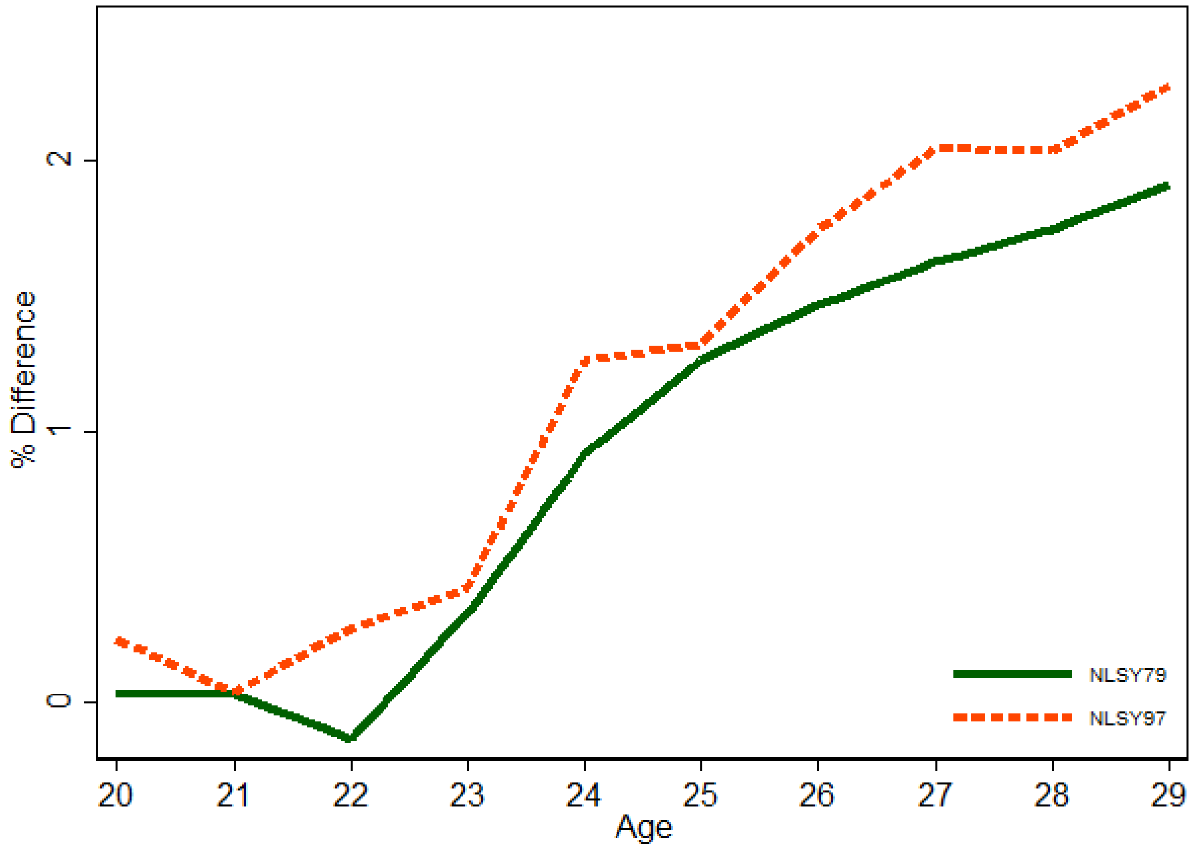
Note: Figure shows estimated effects of 0.1 standard deviation change in AFQT score for representative NLSY79 sample. Horizontal axis shows results for two-year age groupings beginning with age listed (e.g., 30 refers to 30-31 year olds). Estimates are obtained from the coefficient on the computed AFQT Z-score regressed on annual labor incomes (including zeros). These are converted to percentage changes by dividing the estimated effect by the dependent variable mean at the specified age. Background covariates include: gender, race/ethnicity (black, Hispanic vs. Non-Black Non-Hispanics), magazines, library cards and newspapers in home at age 14 (3 variables), urban residence at 14, respondent and respondent's parents foreign born (3 variables), mother and father's education (< high school graduate, some college, college graduate vs. high school graduate), number of siblings (0, 1, 2, 3, 4, ≥5), older siblings (0, 1, 2, 3, ≥4) and survey year dummy variables. Time-varying covariates include values of: marital status (currently married, divorced/separated widowed vs. never married), urban residence, census region (north central, south, west vs. northeast). Non-cognitive variables refer to Rotter, and Rosenberg scales measured in 1979 and 1980, and self-assessed sociability personality (extremely shy to extremely outgoing) at age 6, collected in 1985.

Fig 2: AFQT "Effects" on Annual Labor Income using Alternative Samples



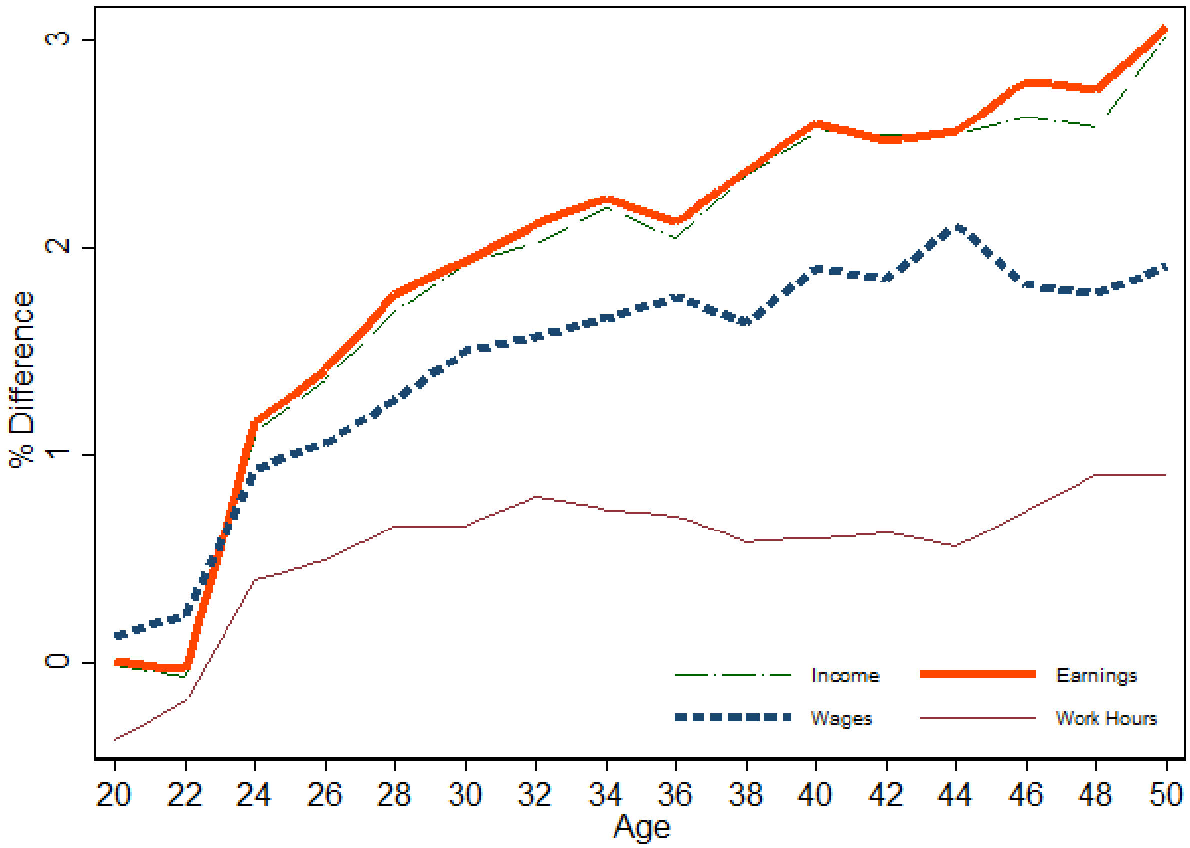
Note: See note on Figure 1. Base specification includes background and time-varying covariates as well as non-cognitive test scores. "Balanced" sample is restricted to respondents with income information provided at age 48. The analysis including oversamples is for all NLSY respondents, including the supplementary samples of nonwhites.

Fig 3: AFQT "Effects" on Annual Incomes using Data from NLSY79 and NLSY97 Cohorts



Note: See note on Figures 1 and 2. This figure shows results for common specifications for 20-29 year olds using data from the NLSY79 and NLSY97 cohorts.

Fig 4: AFQT "Effects" on Alternative Labor Market Outcomes



Note: See note on Figure 1. Specifications include background and time-varying covariates as well as non-cognitive test scores. Data are for the NLSY79 nationally representative sample and refer to annual values, except for log hourly wages based on the main (reference) job in the week prior to the survey. Wages are restricted to the range $1 to $1,000 per hour and work hours to ≤5200/year.

Figure 5: Estimated AFQT "Effects" by Gender

Fig 5a: Annual Labor Income

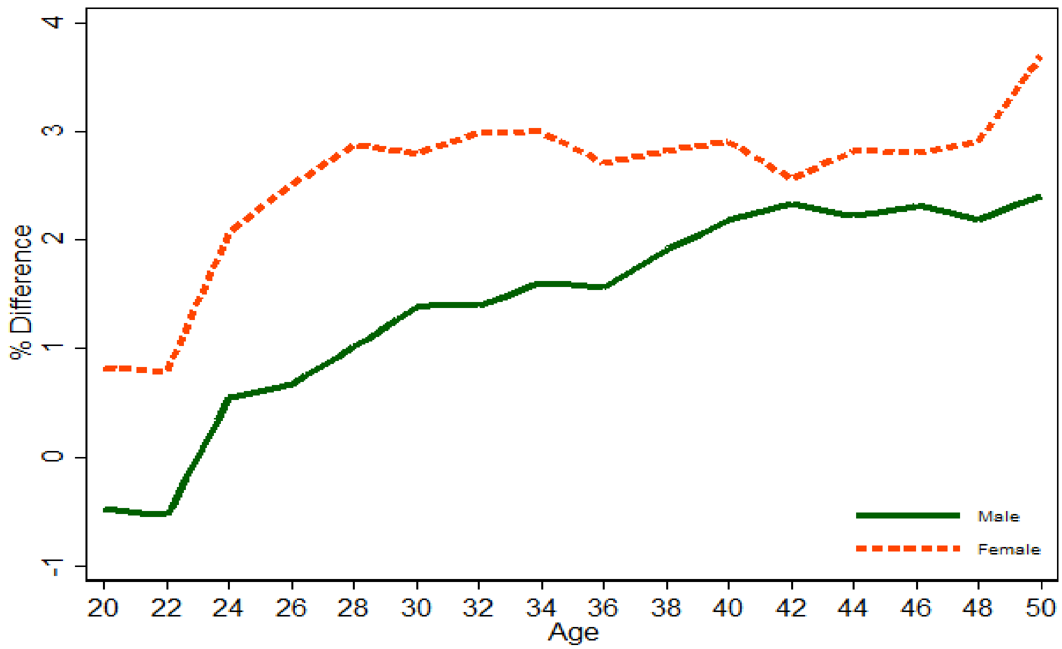


Fig 5b: Hourly Wages

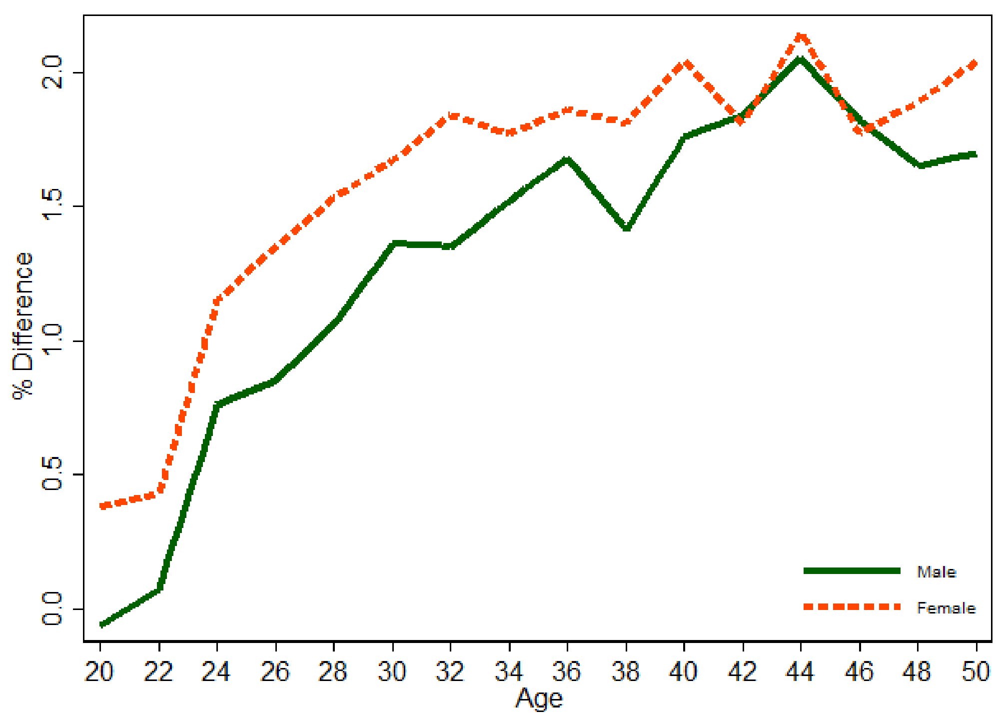


Fig 5c: Annual Work Hours

Figure 6: Estimated AFQT "Effects" by Race/Ethnicity

Fig 6a: Annual Labor Income

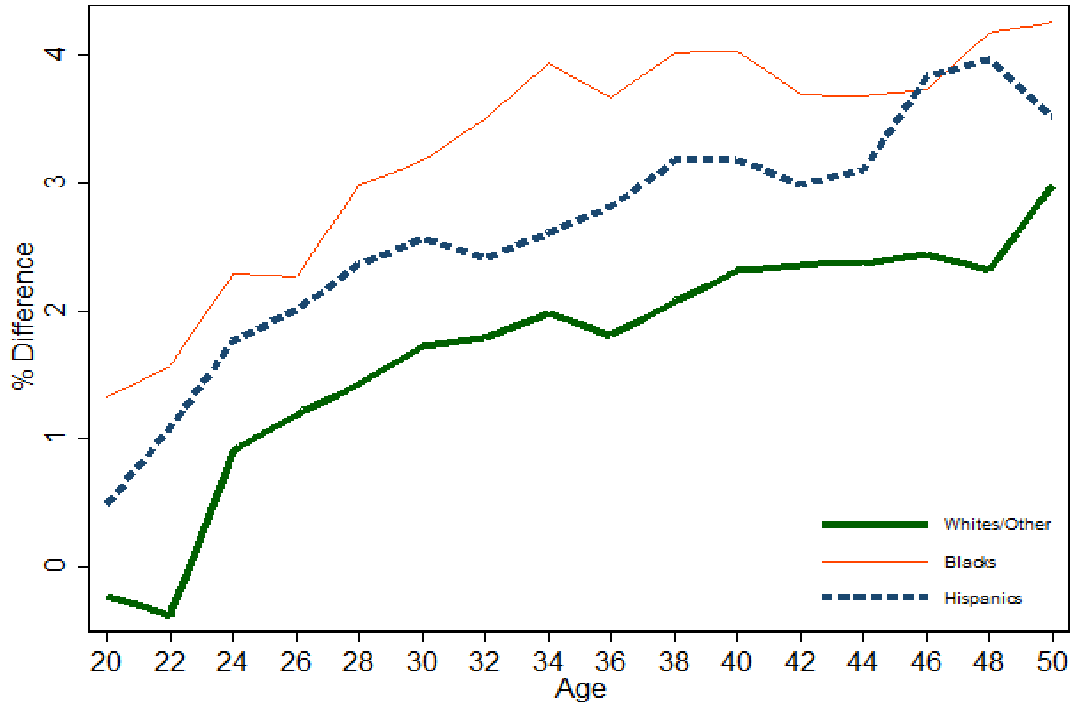


Fig 6b: Hourly Wages

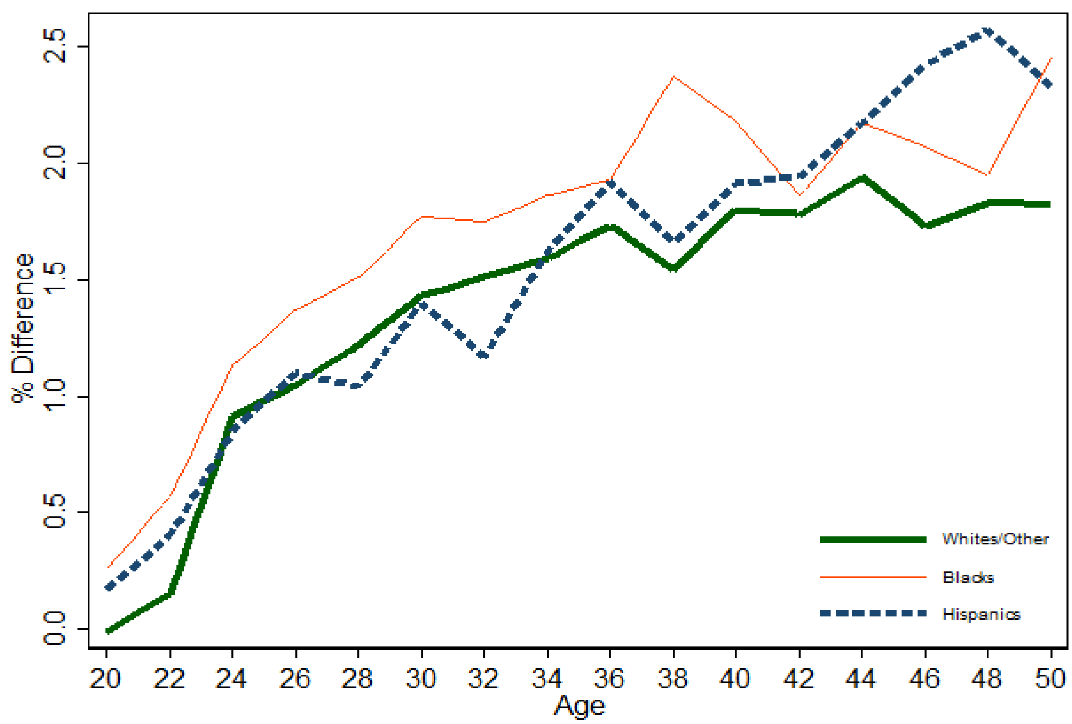
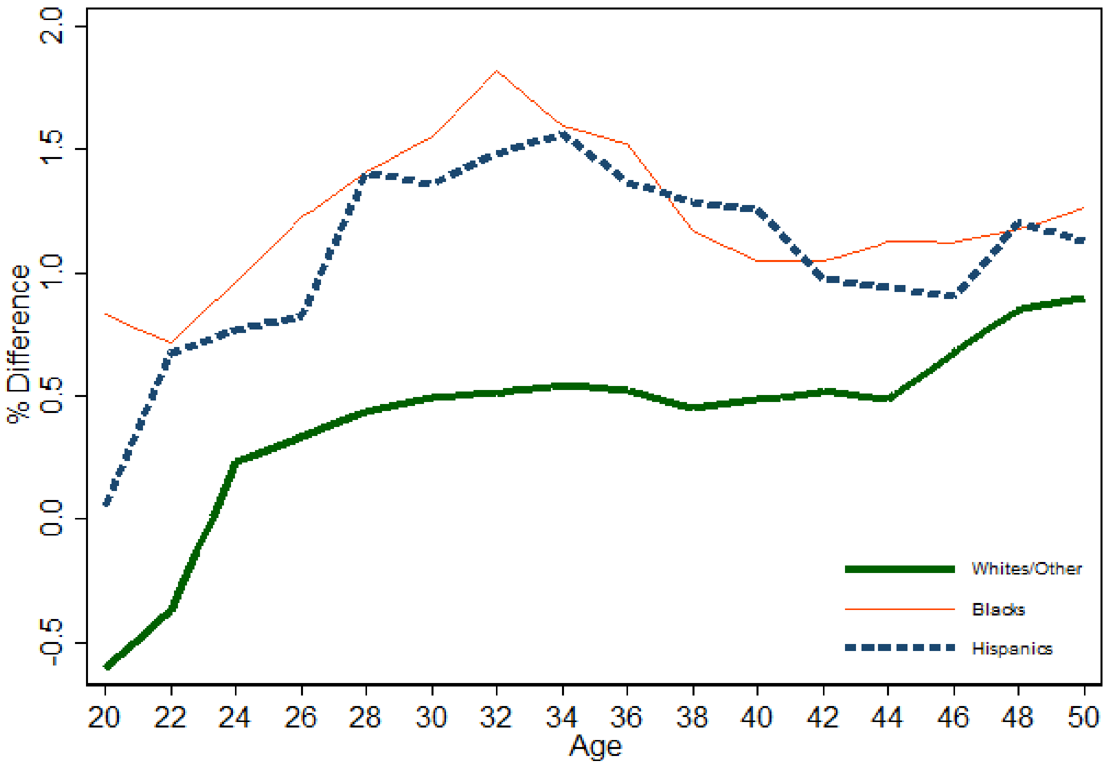


Fig 6c: Annual Work Hours



Appendix A

Table A.1: Descriptive Statistics for Age-Invariant Control Variables

	Representative Sample		Full Sample	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
AFQT	-0.02	1.02	-0.31	1.03
Demographics				
Hispanic	0.07	0.26	0.19	0.39
Black	0.12	0.33	0.30	0.46
Female	0.51	0.50	0.51	0.50
Foreign Born	0.04	0.20	0.07	0.26
Foreign Born Mother	0.07	0.26	0.11	0.31
Foreign Born Father	0.06	0.24	0.10	0.30
Childhood				
Foreign Language in Home	0.14	0.35	0.23	0.42
Magazines in Home	0.65	0.48	0.55	0.50
Newspapers in Home	0.83	0.38	0.74	0.44
Library Card in Home	0.75	0.44	0.70	0.46
Urban Residence at 14	0.77	0.42	0.79	0.41
# Siblings				
0	0.03	0.18	0.03	0.17
1	0.16	0.36	0.13	0.33
2	0.23	0.42	0.20	0.40
3	0.21	0.41	0.19	0.39
4	0.14	0.34	0.14	0.35
5+	0.23	0.42	0.31	0.46
Fraction Missing	0.00	0.03	0.00	0.04
# Older Siblings				
0	0.21	0.41	0.20	0.40
1	0.25	0.43	0.23	0.42
2	0.19	0.40	0.18	0.38
3	0.12	0.33	0.13	0.33
4+	0.16	0.36	0.20	0.40
Fraction Missing	0.07	0.25	0.06	0.24
Mother's Education				
Below High School	0.31	0.46	0.40	0.49
High School Graduate	0.44	0.50	0.37	0.48
Some College	0.10	0.30	0.09	0.28
College Graduate	0.10	0.29	0.07	0.26
Missing	0.05	0.22	0.06	0.24

Father's Education				
Below High School	0.30	0.46	0.36	0.48
High School	0.33	0.47	0.29	0.45
Some College	0.10	0.30	0.08	0.27
College Graduate	0.17	0.37	0.12	0.33
Missing	0.10	0.30	0.15	0.36
Non-cognitive Scores				
Rotter Score	-0.01	1.00	-0.08	1.00
Fraction Missing	0.01	0.09	0.01	0.10
Rosenberg Score	0.00	0.99	-0.05	0.99
Fraction Missing	0.02	0.16	0.03	0.16
Sociability at Age 6				
Extremely Shy	0.16	0.37	0.18	0.38
Shy	0.41	0.49	0.41	0.49
Outgoing	0.25	0.43	0.24	0.43
Extremely Outgoing	0.13	0.33	0.12	0.32
Missing	0.05	0.21	0.05	0.22

Note: Data in the first two columns refer to the national representative sample (n=5,766) and in the next two columns to the full sample, which includes oversamples of blacks and Hispanics (n=9,213).

Table A.2: Descriptive Statistics for Age-Varying Control Variables

Variable	28-29 Year Olds		48-49 Year Olds	
	Mean	Standard Deviation	Mean	Standard Deviation
Marital Status				
Never Married	0.32	0.47	0.12	0.33
Currently Married	0.55	0.50	0.61	0.49
Divorced/Separated/Widowed	0.14	0.34	0.27	0.44
Missing	0.00	0.01	0.00	0.02
Urban/Rural Residence				
Urban	0.76	0.43	0.66	0.47
Rural	0.20	0.40	0.27	0.44
Missing	0.04	0.20	0.07	0.25
Region				
Northeast	0.18	0.39	0.16	0.36
North Central	0.29	0.45	0.29	0.45
South	0.35	0.48	0.38	0.48
West	0.17	0.38	0.17	0.37
Missing	0.01	0.09	0.01	0.08
Education				
Below High School	0.13	0.33	0.08	0.27
High School Graduate	0.44	0.50	0.42	0.49
Some College	0.22	0.41	0.23	0.42
College Graduate	0.22	0.42	0.27	0.44

Note: Data are from the nationally representative NLSY79 sample.

Table A.3: County Level Measures

County Characteristic	Summary Statistics	
	Mean	Standard Deviation
Demographic Characteristics (1970)		
Population density (people/sq. km)	668	2200
Share of black residents	0.11	0.12
Share of families in poverty	0.11	0.08
Share of children with both parents	0.82	0.06
Income per capita (1970 dollars)	3971	922
Gini coefficient on family income	35.28	3.87
Educational Attainment (≥25, 1970)		
Share Less than high school	0.48	0.11
Share High School Graduate	0.32	0.06
Share Some College	0.10	0.03
Share College Graduate	0.10	0.04
Violent crime rate (per 100,000 residents, 1977)		
Rape	8.76	8.37
Murder	28.16	22.15
Robbery	164.46	204.37
Assault	232.50	161.78
Property crime rate (per 100,000 residents, 1977)		
Burglary	1342.49	715.46
Larceny	2671.53	1465.06
Auto-theft	412.32	337.59

Note: Demographic characteristics refer to 1970 and were obtained from the National Historic Geographic Information System (NGIS), except for per capita incomes, which are shown in 1970 dollars and were obtained from the Bureau of Economic Analysis, and Gini coefficients, which were from Nielsen and Alderson (1977). Education attainment refers to persons 25 and older in 1970, and data were also obtained from the NGIS. Crime rates are per 100,000 residents in 1977 and were obtained from Aneja, Donhue and Zhang (2011).

Table A.4: Comparison of Descriptive Statistics for Age-Invariant Controls between Representative NLSY79 and NLSY97 Samples

Variable	NLSY79 Mean	NLSY79 Standard Deviation	NLSY97 Mean	NLSY97 Standard Deviation
AFQT	-0.02	1.02	0.01	1.00
Demographics				
Black	0.12	0.33	0.16	0.37
Hispanic	0.07	0.26	0.12	0.32
Female	0.51	0.50	0.49	0.50
Foreign Born	0.04	0.20	0.04	0.21
Foreign Born Mother	0.07	0.26	0.14	0.35
Foreign Born Father	0.06	0.24	0.13	0.33
Childhood				
Foreign Language in Home	0.14	0.35	0.15	0.36
Urban Residence at 14	0.77	0.42	0.68	0.47
# Siblings				
0	0.03	0.18	0.17	0.37
1	0.16	0.36	0.41	0.49
2	0.23	0.42	0.27	0.44
3	0.21	0.41	0.10	0.31
4	0.14	0.34	0.03	0.17
5+	0.23	0.42	0.02	0.15
Fraction Missing	0.00	0.03	\	\
Mother’s Education				
Below High School	0.31	0.46	0.32	0.47
High School Graduate	0.44	0.50	0.15	0.36
Some College	0.10	0.30	0.17	0.38
College Graduate	0.10	0.29	0.21	0.41
Missing	0.05	0.22	0.15	0.36
Dad's Education				
Below High School	0.30	0.46	0.35	0.48
High School Graduate	0.33	0.47	0.15	0.36
Some College	0.10	0.30	0.24	0.43
College Graduate	0.17	0.37	0.20	0.40
Missing	0.10	0.30	0.06	0.24

Note: Data in the table are for representative NLSY79 and NLSY97 subsamples (n=5,766 and 5,361, respectively).

Table A.5: Cognitive Performance Effects on Lifetime Income through Age 65, with Five percent discount rate

	All	Men	Women	Non-Hispanic White	Non-Hispanic Black	Hispanic
Percentage Change	2.03% (0.15%)	1.56% (0.19%)	2.58% (0.22%)	1.80% (0.16%)	3.45% (0.27%)	2.89% (0.28%)
Lifetime Income NLSY79 Cohort	\$5,113 (378)	\$5,225 (631)	\$4,623 (392)	\$4,852 (426)	\$5,801 (446)	\$5,975 (583)
Lifetime Income for Americans born in 2014	\$8,436	\$8,621	\$7,628	\$8,006	\$9,571	\$9,858
N	3,950	1,860	2,090	3,206	1,892	1,177

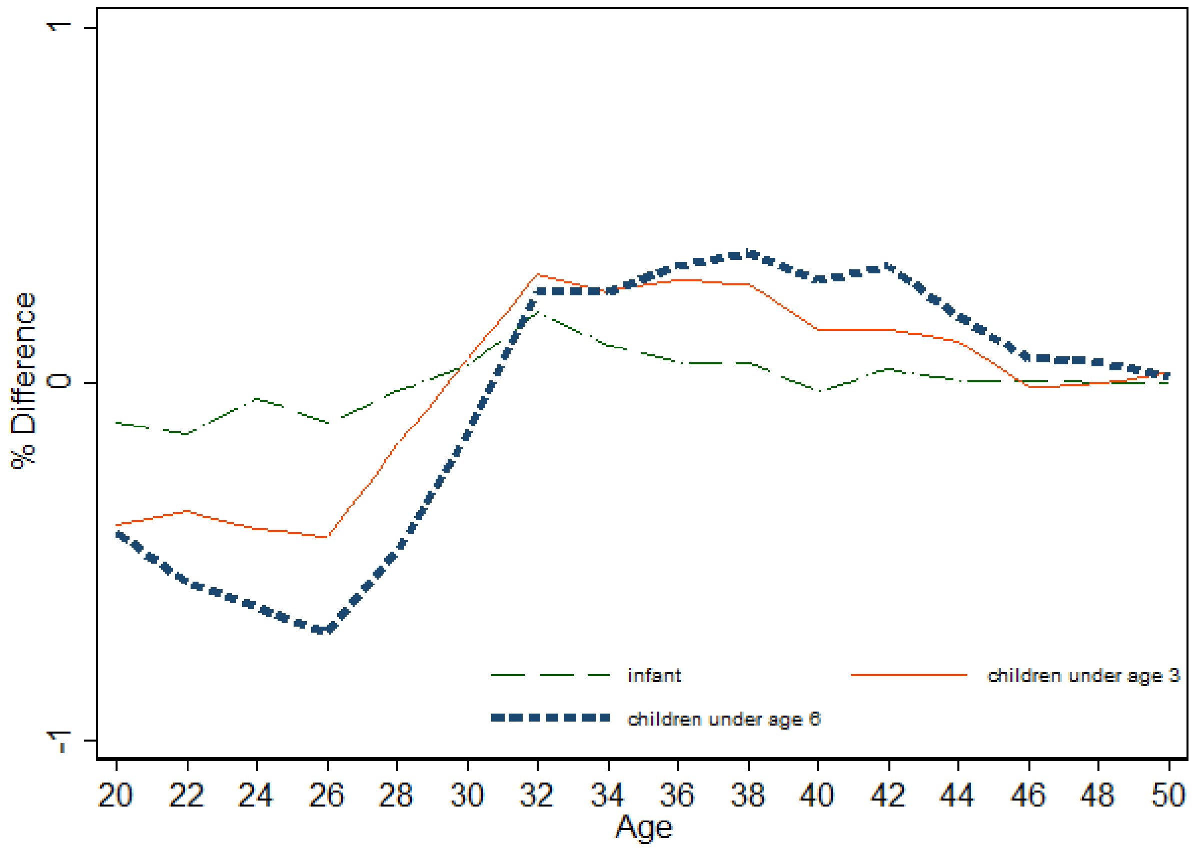
Note: See note on Table 7. The only difference from Table 7 is that we use a discount factor of five percent when constructing the lifetime income variable.

Table A.6: Cognitive Performance Effects on Lifetime Income through Age 65, with Seven percent discount rate

	All	Men	Women	Non-Hispanic White	Non-Hispanic Black	Hispanic
Percentage Change	1.89% (0.14%)	1.40% (0.18%)	2.51% (0.21%)	1.67% (0.15%)	3.29% (0.25%)	2.67% (0.27%)
Lifetime Income	\$2,329	\$2,277	\$2,220	\$2,196	\$2,710	\$2,713
NLSY79 Cohort	(172)	(286)	(182)	(194)	(209)	(270)
Lifetime Income for Americans born in 2014	\$3,842	\$3,757	\$3,663	\$3,623	\$4,472	\$4,476
N	3,950	1,860	2,090	3,206	1,892	1,177

Note: See note on Table 7. The only difference from Table 7 is that we use a discount factor of seven percent when constructing the lifetime income variable.

Figure A.1: Estimated AFQT Effects on Probability of Having Infant/Young Child within Household for Women



Note: The estimates displayed are obtained from linear probability models with an indicator of: (1) presence of infant within household, (2) presence of a child younger than three within the household, (3) presence of a child younger than six within the household, as the outcome variable, respectively. For all ages, we include our preferred set of controls. See note to Table 1 for details.

Appendix B

Table B.1: Construction Details for Key Variables

Variable	Description	Construction Details
Cross-Round Variables		
Rotter-Locus of Control Scale	Extent to which individuals believe they have control over their lives through self-motivation or self-determination (internal control) as opposed to the extent that the environment (that is, chance, fate, luck) controls their lives (external control).	Reverse scores, so that higher scores indicate higher self-control. Then regress reversed scores on quadratic in age (in months). Normalize residual to have mean of zero and standard deviation of one, treating all observations as coming from one cluster and applying sampling weights.
Rosenberg Self-Esteem Scale	Measure the self-evaluation of self-esteem that individual makes and customarily maintains.	Similar to adjusted Rotter score.
Present value of lifetime through age 48	Self-explanatory, two-year age intervals to includes through age 48-49.	Use the constructed total earnings variables and compute the sum of discounted present value of earnings through age 48, assuming a discount factor of 0.03. Individuals are excluded if they not have a valid total income at age 22 or 48, or have 4 or more years of earnings information missing for other ages. Missing values interpolated using information from adjacent ages. Income data before age 20 is discarded because of poor quality and since many respondents were still in school. If valid income data were not available at 20 or 21, imputed income as a fraction of income at 22 is used.
Present value of lifetime through age 65	Present value of lifetime income at birth, up to 65 years of age.	Same as for income through 48. At older ages, income assumed to be the same as the total income at 48.
Age-Specific Variables		
Work flag	An indicator for whether the respondent worked at all during the year.	Variable equals one if respondent worked at least one week in year.
Annual Earnings	Self-explanatory	Total earnings from wage/salary/tips constructed by NLSY team. Valid skips (which take the value of -4) recoded as zeros.

Annual Incomes	Earnings plus incomes from farm/own business.	Combines earning information from two variables: earnings from wage/salary/tips and income from farm/own business. Valid skips (which take the value of -4) recoded as zeros before summation. If farm/own business income not available (due to refusals, don't knows or invalid skips), zeros are used for this component.
Annual Weeks Worked	Self-explanatory	Total number of weeks worked of a calendar year. For observations with missing information, if less than or equal to 10 percent of, work is interpolated using weeks where information is available. Observations dropped if more than 10 percent of the weeks contain missing data.
Annual Work Hours	Self-explanatory	Similar to weeks worked.
Hourly Wages (CPS job)	Hourly wages in reference job.	Variable constructed by the NLSY team without further modifications.
Hourly Wages (constructed)	Annual Earnings divided by annual hours	Defined as the ratio between the annual income and annual work hours, with components defined as described above.

Table B.2: Estimated Cognitive Performance Effects on Annual Incomes

Age	(1)	(2)
28	0.015	0.021
	(0.002)	(0.002)
38	0.024	0.023
	(0.002)	(0.003)
48	0.022	0.032
	(0.003)	(0.004)
Group	Old Respondents	Young Respondents

Note: See note on Table 2. Estimates correspond to column (4) in that table, except that the sample is divided into "old" respondents, born before 1962 and "young" respondents born after 1961. Sample sizes for old respondents at ages 28, 38, 48 are 3021, 2732, 2580 and young respondents at these ages they are 1995, 1761, 1684. Robust standard errors are in parentheses.

Table B.3: Cognitive Performance Effects on Lifetime Incomes, by Date of Birth, Three Percent Discount Rate

	All	Men	Women	Non-Hispanic White	Non-Hispanic Black	Hispanic
Young (born after 1961)						
Percentage Change	2.61%	2.45%	2.56%	2.28%	3.23%	3.24%
	(0.27%)	(0.36%)	(0.38%)	(0.28%)	(0.43%)	(0.51%)
Lifetime Income NLSY79 Cohort	$14,520	$17,489	$10,111	$13,664	$11,588	$14,493
	(1,522)	(2,547)	(1,517)	(1,693)	(1,544)	(2,273)
N	1,553	780	773	1,245	765	485
Old (born before 1962)						
Percentage Change	1.85%	1.24%	2.63%	1.68%	3.79%	2.96%
	(0.20%)	(0.25%)	(0.30%)	(0.21%)	(0.37%)	(0.38%)
Lifetime Income NLSY79 Cohort	$10,123	$9,277	$10,051	$9,755	$13,956	$13,240
	(1,080)	(1,833)	(1,136)	(1,230)	(1,357)	(1,698)
N	2,397	1,080	1,317	1,961	1,127	692

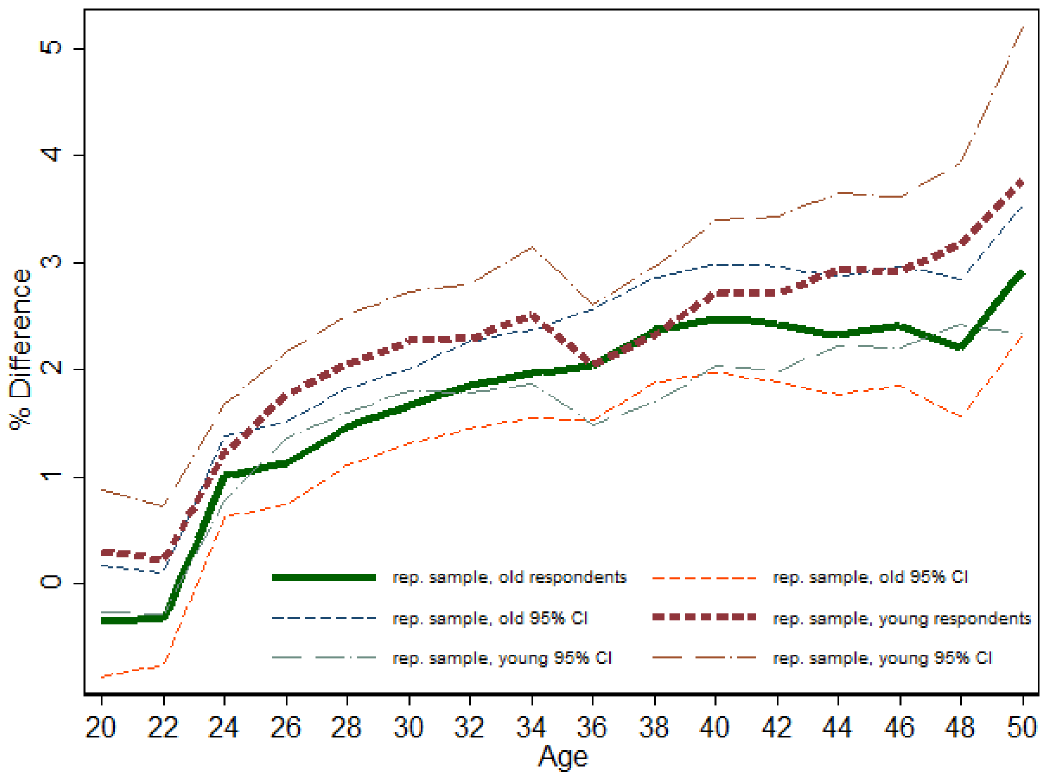
Note: See notes on Tables 2 and 4. Table shows estimated effects of an increase of 0.1 standard deviation in AFQT scores for the representative NLSY79 sample, as a percentage change or dollar amount change on the net present value of the sum of annual incomes from age 20 through age 65 for the specified population group. Lifetime income results are based on incomes discounted to the birth year using an annual discount rate of three percent and expressed in 2014 dollars. For all individuals, men and women, data are from the nationally representative NLSY79 sample. The race/ethnicity estimates use the full sample, including the supplementary samples of blacks and Hispanics. "Whites" refer to non-black non-Hispanics. In addition to AFQT scores, models control for background, age-varying, and non-cognitive characteristics and year fixed-effects. Robust standard errors are shown in parentheses.

Table B.4: Cognitive Performance Effects on Lifetime Incomes, by Date of Birth, Five Percent Discount Rate

	All	Men	Women	Non-Hispanic White	Non-Hispanic Black	Hispanic
Young (born after 1961)						
Percentage Change	2.47% (0.25%)	2.27% (0.33%)	2.53% (0.36%)	2.15% (0.26%)	3.13% (0.41%)	3.06% (0.48%)
Lifetime Income NLSY79 Cohort	$6,285 (647)	$7,364 (1078)	$4,643 (657)	$5,884 (719)	$5,177 (677)	$6,316 (983)
N	1,553	780	773	1,245	765	485
Old (born before 1962)						
Percentage Change	1.73% (0.18%)	1.11% (0.23%)	2.54% (0.28%)	1.56% (0.19%)	3.60% (0.35%)	2.71% (0.35%)
Lifetime Income NLSY79 Cohort	$4,344 (459)	$3,793 (772)	$4,495 (490)	$4,161 (520)	$6,109 (588)	$5,604 (728)
N	2,397	1,080	1,317	1,961	1,127	692

Note: See note on Table B.4.

Figure B.1: Income Effects for Respondents by Age at Which AFQT Scores Were Measured



Note: Table shows predicted effect of 0.1 standard deviation increase in AFQT scores in a model that includes background and time-varying covariates, as well as non-cognitive test scores and year fixed-effects. "Old" respondents are those over 18 at the time of AFQT testing, with "young" respondents being 18 or less when tested.

Figure B.2: Supplementary Wage Results

Fig B.2a: AFQT Score “Effects” on Log Hourly Wages

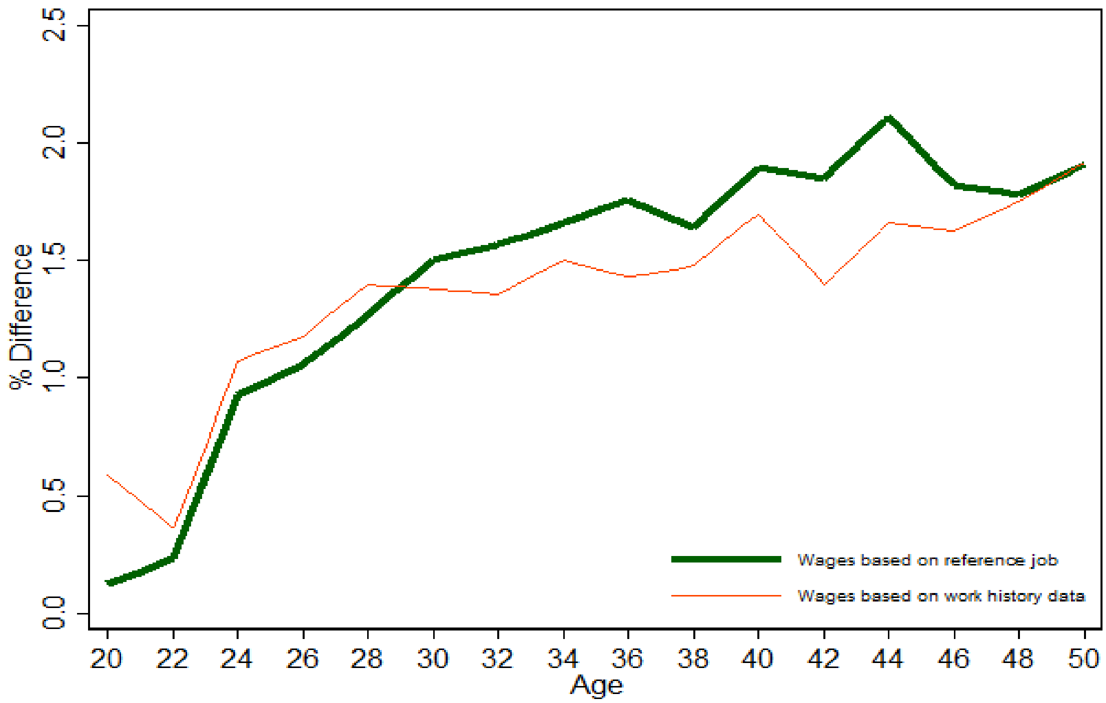


Fig B.2b: AFQT Score “Effects” on Levels and Logs of Hourly Wages

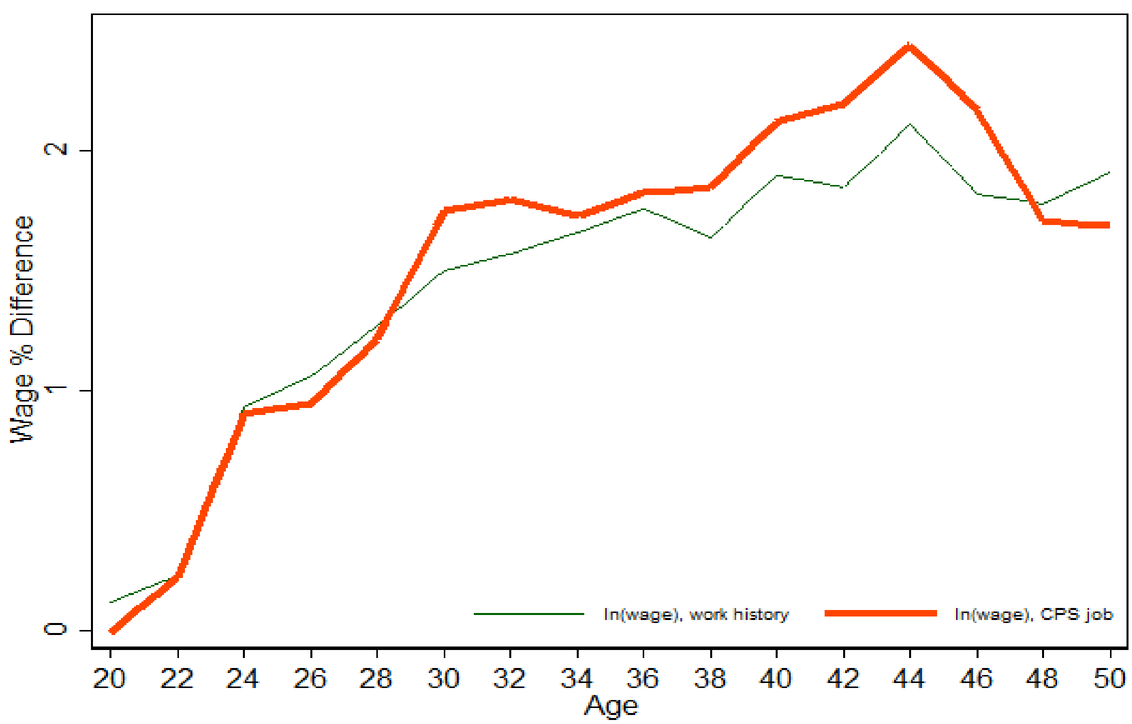
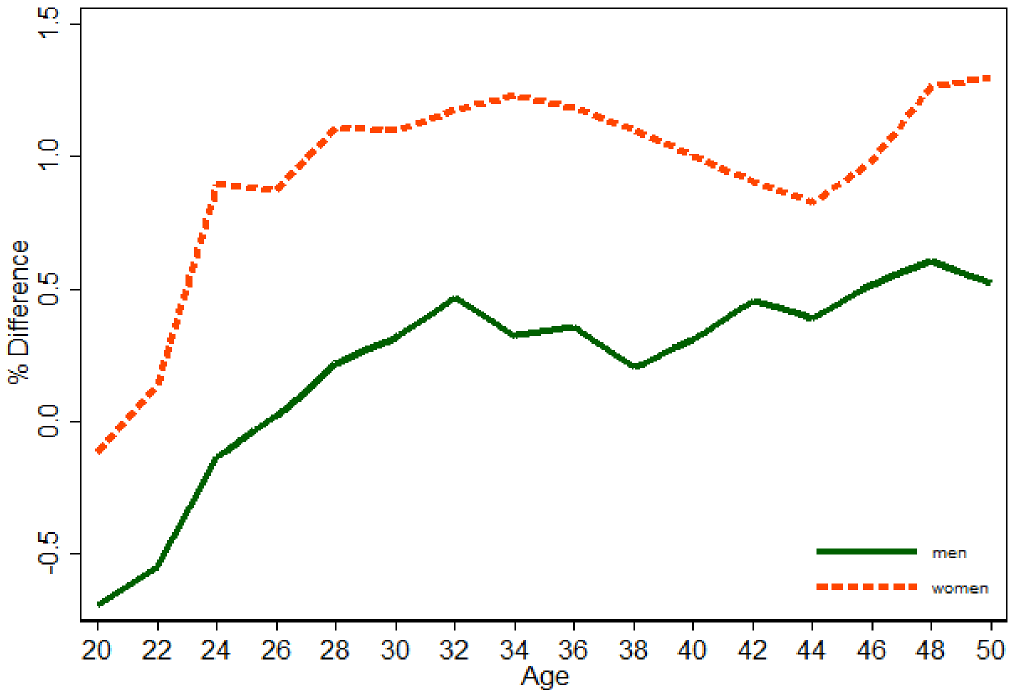
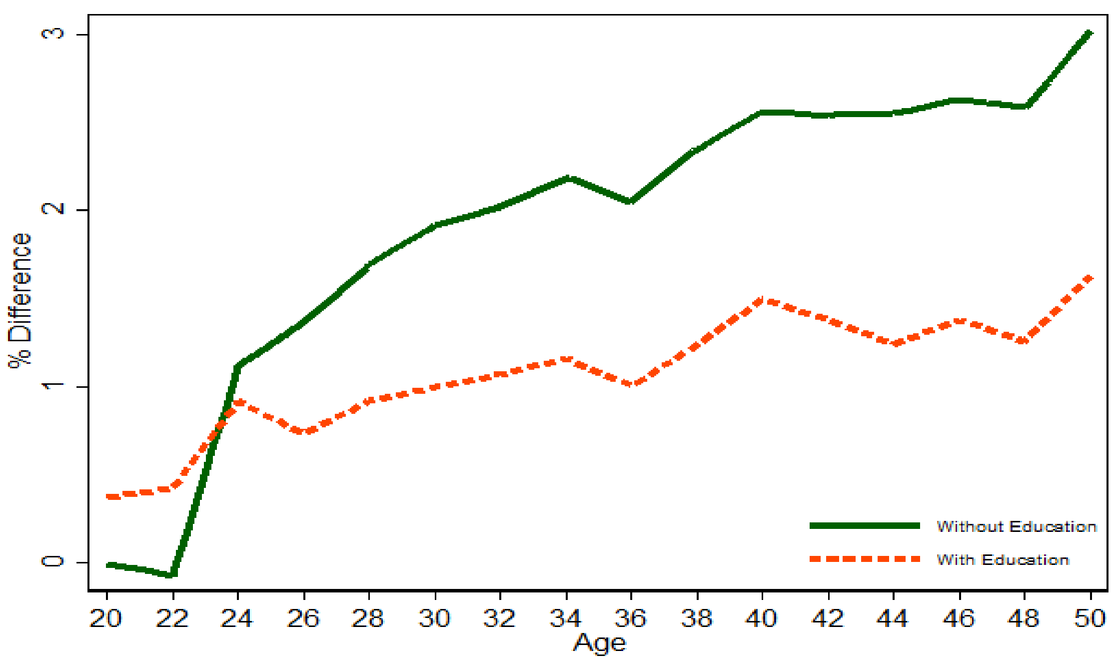


Figure B.3 AFQT Effect on Annual Work Hours by Gender with Controls on Presence of Young Child and Number of Children



Note: Compared to Figure 4c, estimates in this graph are obtained from specifications with two extra controls: an indicator for having a child under the age of three and number of children with the household.

Figure B.4: Estimated AFQT Effects on Annual Incomes, without and with Controls for Education



Note: Education covariates are <12, 12-15, 16 and >16 years of schooling.